An Integrative Model to Predict Scholastic Performance:
Fluid Intelligence, Broad Personality Traits, Narrow Traits, and Their Interplay

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Eidesstattliche Erklärungen

Hiermit versichere ich des Eides statt, dass

- Ich die vorliegende Dissertation mit dem Titel „An Integrative Model to Predict Scholastic Performance: Fluid Intelligence, Broad Personality Traits, Narrow Traits, and Their Interplay" selbständig und ohne unerlaubte Hilfe angefertigt habe.
- Es sich um die Ersteinreichung der vorliegenden Arbeit als Dissertation handelt.
- Ich die Promotionsordnung der Humboldt-Universität zu Berlin zur Kenntnis.

Berlin, den 20.01.2016 Jing Zhang

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Abstract

This dissertation deals with the prediction of scholastic performance in Chinese culture. All in all, three studies were conducted. Two studies focus on personality and test the Big Five Narrow Trait Model (B5NT) which is one of theoretical corner stones of this thesis. The third study includes cognitive ability and focuses on the interplay between personality and ability predicting scholastic performance. Thus, the thesis uses the constructs of fluid intelligence (Gf), broad personality traits (Big Five), narrow personality traits (i.e., self-beliefs and learning approaches), and their complex interplay (moderation and mediation processes) as predictors of scholastic performance. Following a general introduction summarizing the theoretical foundations as well as outlining the derivation of the B5NT, three papers are presented. In the context of Chinese secondary school students, Paper 1 examined the predictive power of figural reasoning as an indicator of Gf and personality traits on school grades in three subjects (i.e., Mathematics, Chinese, and English), and further investigated their potential interactions. Paper 2 integrated the findings of Paper 1 with the aforementioned B5NT. Within the study, the B5NT is empirically tested and compared to an alternative model proposed in earlier work, the Double Mediation model [DM]. Self-beliefs and learning approaches were considered as relevant mediators within those analyses. In this cross-sectional study, the B5NT model was strongly supported, whereas the DM model did not find strong empirical support. In order to empirically verify the underlying processes from a longitudinal perspective, Paper 3 expanded on the B5NT related findings in a three-wave longitudinal panel design. The findings supported the B5NT model and further warranted a revision model in which reciprocal effects from performance to big traits are suggested. Thus, the presented thesis provides a theoretical model explaining the influence of the Big Five on scholastic performance. Moreover, empirical support for the proposed model from cross-sectional and longitudinal data was found. Finally, integrating interactions with cognitive ability rounds off the perspective.

Zusammenfassung

Diese Promotion befasst sich in drei unterschiedlichen Studien mit der Vorhersage schulischer Leistungen in der chinesischen Kultur. Die theoretische Grundlage bildet dabei das Big Five Narrow Trait Modell (B5NT). Die ersten beiden Studien untersuchen die Vorhersagekraft von Persönlichkeit auf schulische Leistungen und testen das B5NT anhand querschnittlicher Daten. Die dritte Studie überprüft im Längsschnitt die Vorhersagekraft kognitiver Fähigkeiten auf schulische Leistungen sowie mögliche Interaktionen mit der Persönlichkeit. Die Arbeit befasst sich demzufolge sowohl mit Konstrukten der fluiden Intelligenz (Gf), den Persönlichkeitsdomänen (Big Five), schmaler gefassten Persönlichkeitskonstrukten (Glaube an sich Selbst, Lernstrategien) sowie dem komplexen Zusammenspiel dieser Konstrukte als Prädiktoren für schulische Leistungen.

Nach einer generellen Einführung und der Herleitung des B5NT Modells werden die drei Studien dargestellt. Studie 1 untersucht bei chinesischen Sekundarschülern figurale Verarbeitungsfähigkeit als Indikator für Gf und Persönlichkeitseigenschaften als Indikatoren für Schulnoten in den Fächern Mathematik, Chinesisch und Englisch sowie mögliche Interaktionen. Die zweite Studie integriert diese Ergebnisse in das B5NT Modell, das zudem mit anderen Modellen, wie etwa dem Double Mediation model (DM), verglichen wird. Der Glaube an sich selbst sowie Lernstrategien werden in den Analysen als wichtige Mediatoren betrachtet. Studie 3 überprüft die Ergebnisse in einem längsschnittlichen Design. Während bereits in Studie 2 starke Evidenz für das B5NT Modell gefunden werden konnte, kann dies auch in Studie 3 repliziert werden. Zudem können in einem Revisionsmodell reziproke Effekte von Performanz auf Persönlichkeitsdomänen angenommen werden. Die Promotion stellt daher ein theoretisches Modell zur Verfügung, das den Einfluss von den Big Five Domänen auf die schulischen Leistungen erklärt und durch querschnittliche sowie längsschnittliche Daten gestützt wird.

General Introduction

Achievement in school is considered as an important prerequisite for adolescents' further education and subsequent successful career (Levpušček & Zupančič, 2009; Schmidt & Hunter, 1998). Identifying powerful predictors of scholastic performance have become an important research domain for decades. There is a great amount of research focusing on the predicting role of intelligence (Gottfredson, 2002; Kuncel, Hezlett, & Ones, 2004), personality (mainly based on the Five-Factor Model: Poropat, 2009; Richardson, Abraham, & Bond, 2012), as well as several narrow constructs, such as self-beliefs (e.g., academic self-concept and academic self-efficacy: Bong & Skaalvik, 2003; Entwistle & Smith, 2002; Marsh & Craven, 2006; Pajares & Schunk, 2001) and learning approaches (e.g., Chamorro-Premuzic & Furnham, 2008; Furnham, Monsen, & Ahmetoglu, 2009). Evidence on their impact on scholastic performance is still emerging. However, these variables have traditionally been considered rarely as integrated parts of the individual, and little is known about their interplay in predicting scholastic performance (i.e., moderation and mediation processes).

Although some researchers have postulated that personality and intelligence might interact with each other to influence performance (Ackerman, 1996; Cattell, 1987; Chamorro-Premuzic & Furnham, 2006; Zeidner, 1995), empirical research in this regard has been rare (Heaven & Ciarrochi, 2012; Ziegler, Knogler, & Bühner, 2009). For example, little is known about explanatory mechanisms of why and how personality traits predict performance (e.g., Corker, Oswald, & Donnellan, 2012; Hair & Graziano, 2003; Shams, Mooghali, & Soleimanpour, 2011) despite the fact that research has consistently shown that personality traits contribute to the prediction of educational performance independent of intelligence (Poropat, 2009; Richardson et al., 2012). Importantly, almost no tangible framework has been provided so far to make these research questions efficient or even valid.

There is ample evidence that personality traits, academic self-efficacy, academic self-concept, and learning approaches are all interrelated (Drew & Watkins, 1998; Judge & Ilies, 2002; Lee, Lee, & Bong, 2014; Marsh & Craven, 2006; Peterson & Whiteman, 2007; Zhang, 2003) and are likely to influence performance across different levels of education. It seems that these variables do not operate separately but form a complex network that brings about changes in performance. Taking these relations into account, Figure 1 contains a synthetic conceptual model for predicting scholastic performance. It also serves as a guiding framework for this dissertation. As can be seen, intelligence and personality traits have direct effects on scholastic performance. Moreover, intelligence and personality traits predict self-beliefs (subject-specific self-efficacy and self-concept) and learning approaches (deep and surface learning approaches), self-beliefs predict learning approaches and scholastic performance, and learning approaches predict scholastic performance. To avoid conceptual uncertainty, this introductory chapter first presents basic definitions of key variables used in this dissertation. In general, the framework is divided into two parts: (1) moderation and (2) mediation processes describing the relations of personality traits to scholastic performance in Mathematics, Chinese, and English. Previous research addressing moderation and mediation processes is reviewed, extant findings in Western cultures summarized, and corresponding limitations noted.

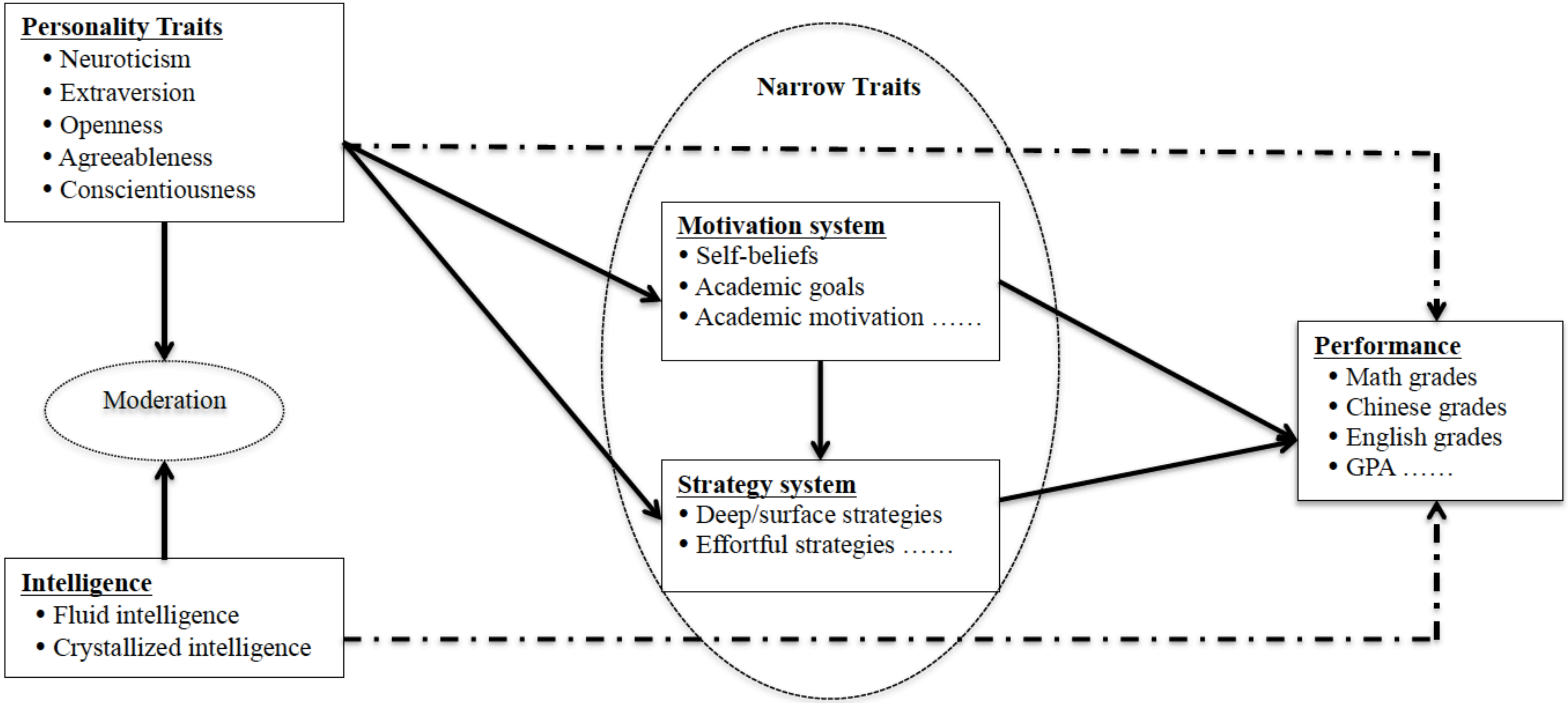

Figure 1. A conceptual model illustrating routes to scholastic performance. Oval shapes represent the central hypothesized processes that underlie the relationships between personality traits and scholastic performance. GPA = grade point average.

Basic Definitions

Intelligence. Intelligence is the amalgamation of processes and knowledge that yield successful solutions to cognitively taxing problems (Ackerman, 1997). There are two major components of intelligence, which are distinguishable and amenable to precise operational or empirical descriptions (Chamorro-Premuzic & Furnham, 2005; McGrew, 2009). McGrew (2009) defined fluid intelligence (Gf) as "the use of deliberate and controlled mental operations to solve novel problems that cannot be performed automatically" (p. 5). Gf is highly related to general intelligence (g), the ability to learn and acquire new knowledge and skills (Ackerman, Beier, & Boyle, 2002; Blair, 2006). Crystallized intelligence (Gc) is defined as "the knowledge of the culture that is incorporated by individuals through a process of acculturation. Gc is typically described as a person's breadth and depth of acquired knowledge of language, information and concepts of a specific culture" (p. 5). Traditionally, intelligence tests were designed to forecast individual differences in achievement, such as educational and occupational performance (in particular school success). A body of research has established that intelligence is the best predictor of educational performance (Gottfredson, 2002; Kuncel et al., 2004).

Personality traits. Contrary to the field of intelligence, most measures of personality are not designed to predict individual differences in maximum performance (Ackerman & Heggestad, 1997), but typical enactments of action, cognition, motivation, and emotion (Fleeson, 2012). Because of the wide acceptance of the Five-Factor Model (Big Five: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness; Goldberg, 1992), a body of evidence has established that the Big Five contributed to scholastic performance (see O'Connor & Paunonen, 2007; Poropat, 2009; Richardson et al., 2012). Consistent findings were often reported for Conscientiousness and Openness to Experience, whereas the findings on the other three Big Five were less consistent.

Conscientiousness. Conscientiousness reflects a tendency to be purposeful, organized, reliable, determined, and ambitious (Digman, 1990). Of the Big Five, Conscientiousness revealed the most consistent medium-sized effects with educational performance (Poropat, 2009; Richardson et al., 2012). Such a relation has often been interpreted in terms of motivation (e.g., Colquitt & Simmering, 1998; Furnham, 1995; Komarraju, Karau, & Schmeck, 2009), which is of considerable importance to educational performance. It therefore seems reasonable that students who are more conscientious are achievement-striving and perform better in education settings.

Openness. Openness demonstrated significant small sizes effects with performance at the secondary and tertiary school level (see Poropat, 2009; Richardson et al., 2012, for reviews). Such significant effects have often been explained by the association between Openness to Experience with intelligence (Ackerman & Heggestad, 1997). It is not surprising that more open students are curious, imaginative, and intelligent (Digman, 1990), as well as motivated to fully understand what they learn (Chamorro-Premuzic & Furnham, 2009; Zhang, 2003). Of note, other research also discussed the possibility that the effect of Openness to Experience might be moderated by the nature of academic settings (Chamorro-Premuzic & Furnham, 2003), and one or more moderators might be responsible for its effects on educational performance (O'Connor & Paunonen, 2007).

Agreeableness. There is evidence that Agreeableness had slightly lower meta-analytic positive correlations with educational performance (Poropat, 2009; Richardson et al., 2012), which can be often explained as greater levels of cooperation with teachers (De Raad & Schouwenburg, 1996). Despite this, Poropat (2009) also pointed out the possibility that when students proceed through their educational career, the positive correlations would decline because of changes in the relationship with teachers. This line of thought is corroborated by the findings from Steinmayr, Bipp, and Spinath (2011) who reported no significant relations with scholastic performance in secondary school students.

Neuroticism. Neuroticism often shows negative relationships with educational performance (see Poropat, 2009, for a review). Neurotic students tend to experience higher levels of anxiety, thereby potentially deteriorating performance (De Raad & Schouwenburg, 1996). However, such negative correlations might become less substantial among older students in primary education (De Raad & Schouwenburg, 1996) and decline again at the secondary level (Poropat, 2009). On the one hand, this pattern may be due to students' upward restriction of intelligence. That is, intelligent students might learn effective strategies to manage their anxiety which, in turn, decreases the effects of anxiety on academic performance (Poropat, 2009) . On the other hand, the negative effects of Neuroticism could be neutralized or even reversed by an indirect effect through academic motivation (De Feyter, Caers, Vigna, & Berings, 2012).

Extraversion. Extraversion reflects positive affect, enthusiasm, a high energy level, and desire to learn (Poropat, 2009). Similar to Neuroticism, Extraversion has produced inconsistent results as a predictor of educational performance. Age seems to be an important moderator in interpreting the relationships between Extraversion and academic performance (De Raad & Schouwenburg, 1996). High levels of Extraversion might be advantageous in elementary school as extravert students may often demonstrate more energy and positive attitudes. On the other hand, Extraversion could also entail more detrimental effects for students attending a higher level of education if they prefer engaging in social activities rather than studying.

Self-beliefs. Educational psychologists have been interested in self-beliefs (i.e., academic self-efficacy and academic self-concept) for a long time. There is an ongoing discussion concerning (a) to what extent they represent two conceptually and empirically different psychological constructs (Bong & Skaalvik, 2003), (b) their relative predictive power for outcome variables such as academic performance (Ferla, Valcke, & Cai, 2009), and (c) their mediating roles in the relations of prior knowledge, gender, and outcome variables (e.g., Pajares & Miller, 1994). Conceptually, academic self-efficacy refers to individuals' beliefs about their abilities to successfully perform their class work (Midgley, Kaplan, & Middleton, 2001) or to master specific academic subjects (Pastorelli et al., 2001). Academic self-concept refers to individuals' knowledge and perceptions about themselves in academic settings (Wigfield & Karpathian, 1991). Despite these clear conceptual definitions, Bong and Skaalvik (2003) still identified several differences regarding their specific elements and level of specificity. Specifically, academic self-efficacy represents one's self-perceived confidence to successfully perform a specific academic task, whereas academic self-concept indicates one's self-perceived ability within a particular academic domain. Regarding level of specificity, academic self-efficacy questionnaires most often refer to specific school tasks, while academic self-concept questionnaires typically refer to specific school subjects. However, an argument could be made that self-efficacy can be measured on a broad or on a task-specific level depending on the correspondence between self-efficacy and performance criteria. When performance of broader scope is predicted (e.g., course grades and overall grade point average), self-efficacy at broader levels should be assessed (e.g., Bandura, 2006; Pajares & Miller, 1995).

Prior research has established the independent predictive power of academic self-efficacy and academic self-concept to a number of academic outcomes such as academic motivation (e.g., Schunk, 1991), learning strategies (Drew & Watkins, 1998; Liem, Lau, & Nie, 2008), and academic achievement (Bong, Cho, Ahn, & Kim, 2012). Moreover, these relations appear to be domain-specific: Self-beliefs in one domain (i.e., Math self-efficacy) are more strongly associated with performance in that domain (i.e., Math grades) than in other domains (Chen & Zimmerman, 2007; Marsh & Seaton, 2012). However, studies are scarce that have examined the relations between academic self-efficacy and specific scholastic performance, and have instead emphasized Math self-efficacy (e.g., Morony, Kleitman, Lee, & Stankov, 2013; Pietsch, Walker, & Chapman, 2003).

Learning approaches. A learning approach reflects enduring and stable strategies of processing information (Snyder, 1999) and is another predictor of academic performance (Biggs, 1978; Chamorro-Premuzic, & Furnham, 2008). Biggs, Kember, and Leung (2001) distinguished two major learning approaches that were likely to enhance learning from a common framework of motive (why students learn) and strategy (how students learn). The first is a *deep learning* approach (deep motive and deep strategy), which involves seeking a real understanding of what is learned. The second is a *surface learning* approach (surface motive and surface strategy), which involves seeking only a reproduction of what is taught. Deep learners are characterized by intrinsic motivation, a search for meaning, and a desire to maximize understanding. They are really interested in the specific learning tasks. Surface learners are characterized by extrinsic motivation and a search for meeting the minimum requirements. They tend to allow shallow cognitive strategies to complete learning tasks as the most minimum of effort possible.

In terms of motive and strategy aspects of learning approaches, previous work has typically shown positive correlations between a deep approach and academic performance, and negative correlations between a surface approach and academic performance (Chamorro-Premuzic & Furnham, 2008; Duff, Boyle, Dunleavy, & Ferguson, 2004; Furnham et al., 2009). However, some studies also demonstrated that a deep approach did not necessarily predict higher academic performance, depending on what the assessment procedure rewards: conceptual understanding or factual knowledge (e.g., Diseth, 2003; Entwistle, Tait, & McCune, 2000).

Moderating Processes

Intelligence-Personality associations. Historically, domains of intelligence and personality traits have been considered mainly in isolation and rarely as integrated parts of the individual. However, their interface, especially the relationship between Openness and intelligence, has been the focus of many studies (e.g., Ackerman & Heggestad, 1997; Poropat, 2009). Their overlaps lead individual difference researchers to adopt one of three perspectives about the relationships between intelligence and personality traits (see Figure 2): (1) Independence, emphasizing that both constructs are independent conceptually and empirically; (2) Associations at the measurement level, assuming that personality traits influence performance on intelligence tests, in some instances leading to individual differences in response accuracy and speed; and (3) Associations at the conceptual level, postulating that personality traits affect when, how, and where individuals apply and invest their cognitive ability. The last approach is believed to be a promising avenue for integrating achievement-related individual differences in both personality and intelligence.

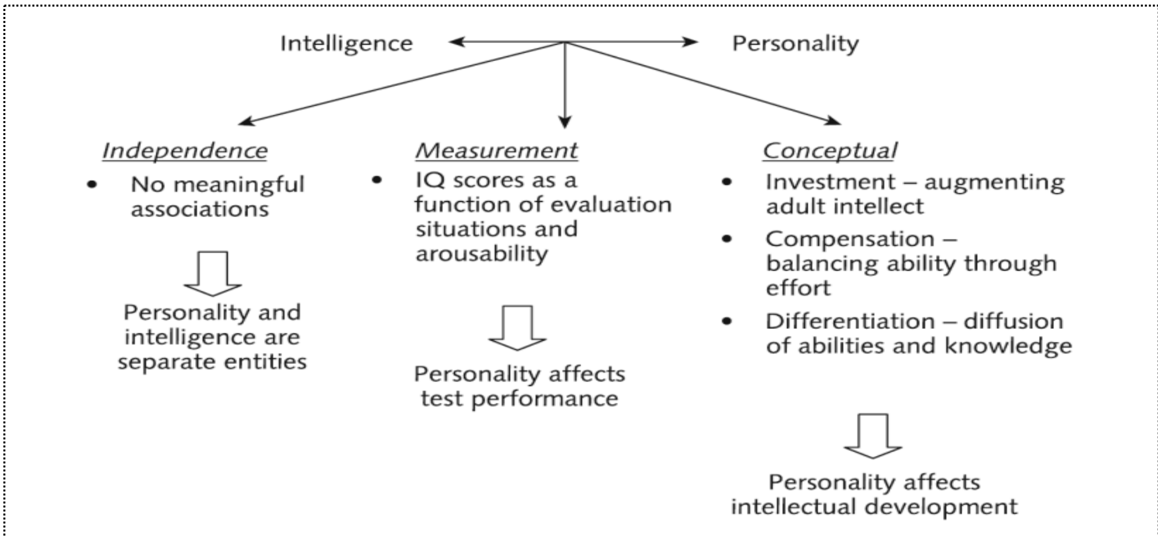

Figure 2. Theoretical perspectives on Intelligence-Personality associations. Adapted from "Re-Visiting Intelligence-Personality Associations Vindicating Intellectual Investment" by Von Stumm, S., Chamorro-Premuzic, T., & Ackerman, P., 2011, in *The Wiley-Blackwell handbook of individual differences* (1st ed., p.219), edited by Chamorro-Premuzic, T., Von Stumm, S., & Furnham, A. John Wiley & Sons.

Interaction hypotheses. In terms of their predictive power of performance, some researchers proposed that performance in work and academics might be determined by factors relating to the capacity to perform (i.e., knowledge, skills, and intelligence), the opportunity to perform, which is affected by environmental constraints such as socioeconomic resources, and the willingness to perform (i.e., motivation, cultural norms, and personality) (Blumberg & Pringle, 1982; Traag, van der Valk, van der Velden, de Vries, & Wolbers, 2005). It seems that if people are capable of doing something, this does not necessarily imply that they are actually willing to tap their potentials. Therefore, both intelligence and personality traits need to be considered simultaneously when predicting academic performance. Moreover, both individual differences variables as performance predictors could be a circular rather than linear process.

According to the aforementioned third perspective, there might be a compensatory relationship between intelligence and personality traits in predicting scholastic performance: balancing ability through efforts (a very famous Chinese proverb). For example, "less" intelligent students may become increasingly more conscientious to compensate for their lack of cognitive ability, whereas more intelligent students can rely to a greater extent on their intelligence and thus "afford" to be less dutiful and organized but nevertheless excel (Chamorro-Premuzic & Furnham, 2005). In fact, such an idea can be traced back to early work models generally positing that job performance is a function of ability and motivation (e.g., Maier, 1958; Mount, Barrick, & Strauss, 1999; Sackett, Gruys, & Ellingson, 1998). Additionally, a previous meta-analysis has established small-to-moderate correlations between personality traits and motivation criteria (Judge & Ilies, 2002). Further, Denissen and Penke (2008) examined motivational reaction norms underlying the Big Five and hypothesized the differences in the tenacity to pursue goals under difficult circumstances as the motivational root of Conscientiousness. Since personality traits are closely linked to motivation, and motivation and ability have been theorized as interacting to influence performance, it could be expected that personality traits, in particular Conscientiousness, enhance the impact of intellectual abilities when predicting scholastic performance. Statistically, this corresponds to a moderation effect such that certain traits moderate (here: increase) the associations between intelligence and performance.

How have moderation effects been studied so far? When predicting educational performance, evidence for an interaction between personality traits and intelligence has produced encouraging but conflicting results. Ziegler et al. (2009) examined the moderating roles of Conscientiousness and its facet achievement striving on the relation between intelligence and GPA (grade point average) in a sample of German psychology students. In the total sample, neither Conscientiousness nor its facet achievement strivings had a significant interaction effect with intelligence. However, in a subsample of high performers, there was an enhancing effect via Conscientiousness. Clearly, their findings contradict the compensatory relationship of Conscientiousness and intelligence mentioned above. Instead, Ziegler, Danay, Heene, Asendorpf, and Bühner (2012) proposed the Openness-Fluid-Crystallized-Intelligence (OFCI) model, a process model integrating Openness, Gf, and Gc. They found a compensatory relationship of Openness and Gf: one of both traits is sufficient to gain Gc. So the other trait does not add to the variance explained when one trait is already high. Conversely, Heaven and Ciarrochi (2012) focused on the interaction of personality and intelligence among high school students and found a positive interaction between Openness and cognitive ability to predict scholastic performance across different school subjects. It appears that being interested in ideas and thinking is not enough to get better school grades as one also needs higher level of intelligence. Their findings contradict that of Ziegler et al. (2012) who found a negative interaction between Openness and Gf in predicting Gc.

Clearly, previous research examining the interaction between personality traits and intelligence mainly focused on one of the Big Five domains, and the findings are not always consistent across different samples. Moreover, prior studies were often conducted in Western cultures, and little is known about the same relations and processes in Chinese culture, which may limit the generalizability of prior findings. Intercultural studies have reported systematic differences between Asian and Western students from preschool to college. For example, Chinese parents get more involved in their children's learning. More specifically, Chinese parents and even teachers emphasize more efforts than innate abilities and encourage students to work hard to compensate for the lack of their innate ability (Tong, Zhao, & Yang, 1985). As such, one would assume that Chinese parenting practices might result in different predictive patterns in terms of intelligence, personality traits, and their interaction than in Western cultures. Therefore, more research using Asian and Western samples are required to provide a comprehensive picture of the complex interplay of personality and intelligence in predicting scholastic performance. To fill in these gaps, **Paper 1** attempted to replicate the specific effects of figural reasoning as an indicator of Gf and the Big Five domains on scholastic performance in Math, Chinese, and English, as well as further to investigate their interaction effects in the context of 836 Chinese secondary school students. In addition, for the interaction hypotheses, latent moderated structural equation models (Klein & Moosbrugger, 2002) were used, which are more robust compared to regular hierarchical regression analyses.

Mediating Processes

The findings derived from **Paper 1** replicated the specific effects for Gf and some of the personality domains on scholastic performance found in Western cultures. However, the questions arise why students' personality traits influence scholastic performance and whether this specific mechanism is consistent across different school subjects. **Papers 2** and **3** aimed to answer these questions. There is a great amount of empirical support for the bivariate associations between personality traits, self-beliefs (i.e., academic self-efficacy and academic self-concept), and learning approaches (Drew & Watkins, 1998; Judge & Ilies, 2002; Lee et al., 2014; Peterson & Whiteman, 2007; Zhang, 2003), as well as their influences on scholastic performance (e.g., Bong & Skaalvik, 2003; Entwistle & Smith, 2002; Marsh & Craven, 2006; Poropat, 2009). Consequently, it is plausible to expect that the relationships between personality traits and scholastic performance might be indirect, and in fact mediated by self-beliefs and learning approaches.

Integrative theories. The idea is derived from the analysis level model of Personality (Graziano, Jensen-Campbell, & Finch, 1997; McAdams, 1995; McAdams & Pals, 2006) and the surface-core traits theory (Marsh & Craven, 2006). Both theories view broad personality traits (i.e., the Big Five) and narrower constructs (e.g., self-beliefs and learning approaches) as different layers of personality, whereby self-beliefs and learning approaches operate at an intermediate level between broad traits and specific behavior (see also Caprara, Alessandri, Di Giunta, Panerai, & Eisenberg, 2010). As such, it can be assumed that personality traits exert their influences on scholastic performance indirectly via core traits (e.g., self-beliefs and learning approaches). Figure 3 depicts such a specific process model (Big Five-Narrow Traits model) in which personality traits exert their influences on scholastic performance indirectly and simultaneously via self-beliefs and learning approaches.

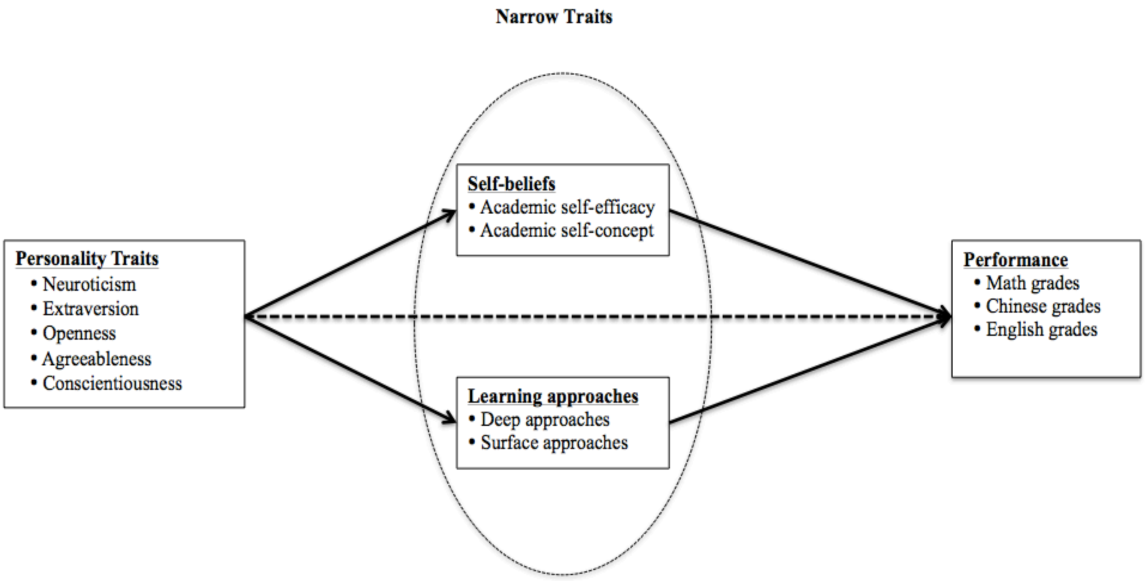

Figure 3. Big Five-Narrow Traits model. *Note*. The model includes the direct paths from all the Big Five domains to self-beliefs and learning approaches. Moreover, all the Big Five domains indirectly influence school grades in Mathematics, Chinese, and English simultaneously via self-beliefs and learning approaches. Dashed-lined arrows specify the direct effects.

Moreover, this idea may also benefit from Mumford and Gustafson's (1988) perspective, assuming that, on the one hand, personality traits could facilitate or inhibit the effective use of strategies and thus improve or deteriorate performance. This clearly represents the aforementioned Big Five-Narrow Traits model. On the other hand, personality traits could provide the motivational impulses or the motivational blocks to use or not to use learning strategies and thus to improve or turn down performance. Therefore, personality traits might also affect scholastic performance via two subsequent mediators (i.e., the Big Five → subject-specific self-efficacy/self-concept → deep/surface learning approach → scholastic performance). Figure 4 presents such a Double Mediation model. First, *personality* should have an influence on *subject-specific self-efficacy and subject-specific self-concept*. Second, self-beliefs should influence *deep and surface learning approaches* as learning approaches are motivated (Pintrich & De Groot, 1990). Finally, students' learning approaches should have direct effects on *scholastic performance*.

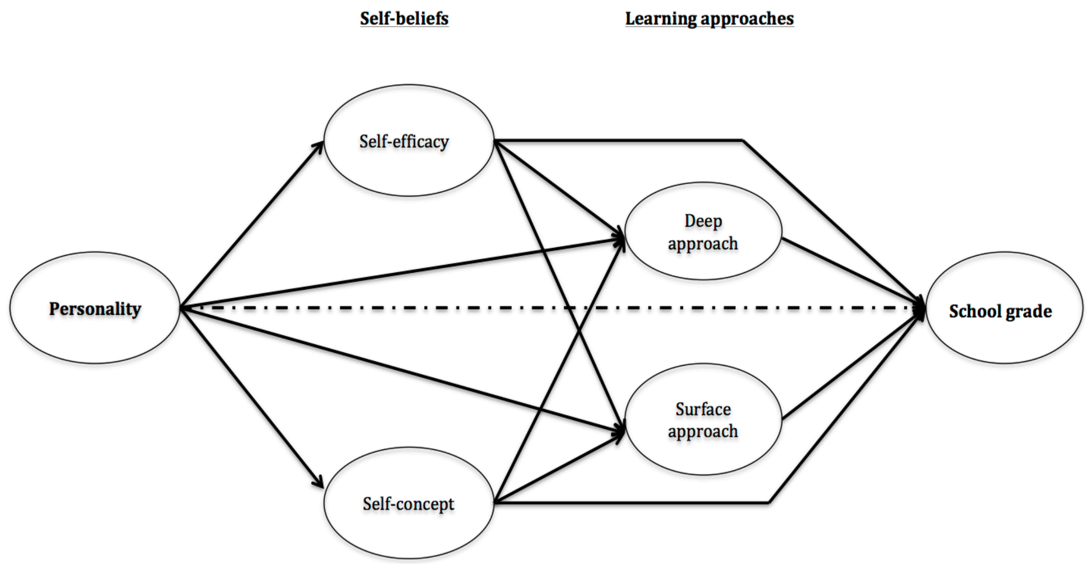

Figure 4. Double Mediation model. *Note*. The Big Five will predict school grades in Mathematics, Chinese, and English directly and indirectly via self-beliefs and learning approaches. Moreover, the Big Five will influence learning approaches directly and indirectly via self-beliefs. Self-beliefs will predict school grades directly and indirectly via learning approaches.

How have mediation effects been studied so far? Evidence for potential mediating processes can be deemed preliminary. For example, the effects of Openness and Conscientiousness on scholastic performance were positively mediated by a deep learning approach but negatively by a surface learning approach (Chamorro-Premuzic & Furnham, 2009; Shokri, Kadivar, Valizadeh, & Sangari, 2007; Swanberg & Martinsen, 2010). In addition, Openness and Agreeableness influenced scholastic performance indirectly via academic self-esteem (Hair & Graziano, 2003) and academic self-efficacy (Shams et al., 2011). Of note, these studies only emphasized a single mediator, and some of them only examined one of the Big Five domains. Therefore, the relations between the Big Five domains and more importantly the exact processes by which they affect scholastic performance remain unclear as the overlap between the variables is not fully controlled for. Moreover, none of the studies explored the possibility that personality traits might influence scholastic performance indirectly via two subsequent mediators. To my best knowledge, the study by Corker et al. (2012) is one of the first attempts to simultaneously examine the mediating roles of effortful strategies and achievement goals in the relations of Conscientiousness and academic performance. In addition, prior studies were conducted using primarily college students, adopting GPA or only Math achievement as academic outcomes. Thus, the specific mechanism in different school subjects has been neglected in previous research.

To address those gaps, **Paper 2** extended the empirical support within two theoretical models that integrate the Big Five with self-beliefs and learning approaches-related processes that lead to scholastic performance: Big Five-Narrow Traits model (B5NT; Figure 3) and Double Mediation model (DM; Figure 4). **Paper 2** is notable for its multi-measure, but it involves the simultaneous measurement of the Big Five and narrow traits. To verify these theoretical assumptions, **Paper 3** further evaluated the B5NT model in a three-wave longitudinal design covering a time span of 1 year.

Aims and Research Questions of the Current Dissertation

The present work attempted to test two major objectives. First, as much of prior research on the topic was conducted in Western cultures, this work aimed to investigate the specific influences of intelligence and the Big Five on scholastic performance in Mathematics, Chinese, and English and further to explore their potential interaction effects in predicting scholastic performance in Chinese cultures. It is expected that the importance of intelligence and the Big Five would vary between Western and Chinese cultures and also vary in different subjects in terms of diverging subject characteristics. Second, a process model was tested to explain why personality traits predict scholastic performance in both cross-sectional and three-wave longitudinal research designs that integrates different variables which have often been investigated separately in previous research (while excluding intelligence from all variables in the models).

Several research questions were formulated:

1. To what degree do students' Gf and personality traits predict their scholastic performance in Chinese culture? Are these effects consistent across different school subjects (i.e., Mathematics, Chinese, and English)?
2. Are there any interaction effects between Gf and personality traits in predicting scholastic performance? If so, are the interaction effects consistent across different subjects?
3. Why and how do students' personality traits affect their scholastic performance? Are the mechanisms subject-specific?
4. Since mediation processes develop over time, are there longitudinal mediation effects from personality traits to scholastic performance?

Why is it so important to explore moderation and mediation effects?

First, exploring possible moderation and mediation processes that integrate the aforementioned variables will yield better insight into the prediction of scholastic performance. Second, exploring the relationships between a wide range of variables we label as antecedents, moderators, and mediators would further contribute to defining a conceptual framework, or nomological network (Cronbach & Meehl, 1955), for predicting scholastic performance (see Figure 1). Such an integrative model unifying several areas of research on scholastic performance into a single, coherent framework provides a foundation for future theory, research, and practice in this emerging area. Third, such an integrative model is consistent with the above-mentioned analysis level of personality perspective (Graziano et al., 1997; McAdams, 1995; McAdams & Pals, 2006), surface-core traits theory (Marsh & Craven, 2006), and Mumford and Gustafson's (1988) perspective. Additionally, this work was conducted in Chinese culture, which would provide comparable evidence on the roles of cognitive and non-cognitive factors in predicting scholastic performance to that in Western cultures.

For practical purposes, this work could provide the foundation for academic interventions through an analysis of possible moderation and mediation effects in a large sample of Chinese secondary school students. To be more specific, the unique effects of Gf and the Big Five on scholastic performance are evaluated. Furthermore, the interactive effects between the Big Five and Gf in predicting scholastic performance are tested, as are the mediation effects of self-beliefs and learning approaches in the relations of the Big Five with scholastic performance. Understanding how these relations may differ between different subjects can inform educators to develop effective intervention programs that improve students' scholastic performance.

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Interaction Effects between Openness and Fluid Intelligence Predicting Scholastic Performance

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Abstract: Figural reasoning as an indicator of fluid intelligence and the domains of the Five Factor Model were explored as predictors of scholastic performance. A total of 836 Chinese secondary school students (406 girls) from grades 7 to 11 participated. Figural reasoning, as measured by Raven's Standard Progressive Matrices, predicted performance in Math, Chinese, and English, and also for a composite score. Among the personality domains, Openness had a positive effect on performance for all subjects after controlling for all the other variables. For Conscientiousness, the effects were smaller and only significant for Math. Neuroticism had a negative effect on Math grades. The effects of Extraversion on all grades were very small and not significant. Most importantly, hierarchical latent regression analyses indicated that all interaction effects between Openness and figural reasoning were significant, revealing a compensatory interaction. Our results further suggest that scholastic performance basically relies on the same traits through the secondary school years. However, importance is given to interaction effects between ability and personality. Implications along with limitations and suggestions for future research are discussed.

Keywords: fluid intelligence; Five Factor Model; Openness to Experience; scholastic performance; latent interaction effect; personality-intelligence interface

Educational success plays an important role in students' future opportunities and success in later life (Ceci & Williams, 1997). Although general intelligence is known to be the strongest predictor of educational and scholastic performance (Deary, Strand, Smith, & Fernandes, 2007; Gottfredson, 2002; Kuncel, Hezlett, & Ones, 2004), other research has identified several non-cognitive factors that are of importance as well, e.g., motivation, school anxiety, and interests, but especially the Five Factor Model (FFM) of personality (Bratko, Chamorro-Premuzic, & Saks, 2006; Greene, Miller, Crowson, Duke, & Akey, 2004; Laidra, Pullmann, & Allik, 2007; Lu, Weber, Spinath, & Shi, 2011; Spinath, Freudenthaler, & Neubauer, 2010; Spinath, Spinath, Harlaar, & Plomin, 2006; Steinmayr, Bipp, & Spinath, 2011). Across different levels of education, the domains of the FFM have been shown to contribute to the prediction of performance independent of intelligence (Poropat, 2009; Richardson, Abraham, & Bond, 2012). Moreover, small-sized correlations between intelligence and personality traits have consistently been reported (Ackerman & Heggestad, 1997; Poropat, 2009). Therefore, it is reasonable to look at intelligence and the domains of the FFM simultaneously in order to control for their shared variance and to identify specific contributions to performance.

Most previous studies addressing the prediction of scholastic performance have been conducted in Western cultures, and little is known about effects in other cultures (e.g., Asian cultures). This is especially important because previous intercultural research has reported systematic differences between Asian and Western students from preschool to college. For example, Chinese people are reported to put more emphasis on hard work compared to innate ability, and believe that knowledge depends on accumulation. Moreover, Chinese students are also reported to believe that success comes from hard work, and show higher achievement motivation than their Western peers (Dweck & Molden, 2005; Tong, Zhao, & Yang, 1985; Tweed & Lehman, 2002). Considering these differences, it can be assumed that the effects regarding scholastic performance reported in Western cultures do not necessarily replicate in Chinese samples. Consequently, the present study aimed at examining the explanatory power of intelligence and the domains of the FFM on scholastic performance in a Chinese sample, and further exploring their potential interactions (Furnham & Monsen, 2009; Ziegler, Cengia, Mussel, & Gerstorf, 2015; Ziegler, Danay, Heene, Asendorpf, & Bühner, 2012).

Fluid Intelligence and Scholastic Performance

In order to understand the influence of intelligence on scholastic performance, it is important to clarify the distinction between fluid intelligence (Gf) and crystallized intelligence (Gc) (Cattell, 1963; Cattell, 1987; McGrew, 2009). Fluid intelligence (Gf) is defined as "the use of deliberate mental operations to solve novel problems that cannot be performed as a function of simple memorization or routine behavior" (Primi, Ferrão, & Almeida, 2010). Also, Gf is considered as a very good proxy for general intelligence (*g*) (Ackerman, Beier, & Boyle, 2002; Blair, 2006), and is often measured with tests such as the Progressive Matrices or Cattell's Culture Fair test (Colom & Garcıa-López, 2002; Furnham, Forde, & Cotter, 1998). Many prior studies mainly focused on the prediction of Mathematics performance and showed that broad cognitive abilities (*i.e.*, fluid reasoning, Gc, and processing speed) were important predictors, speaking to the cognitive complexity of Mathematics (McGrew, 2008; Taub, Floyd, Keith, & McGrew, 2008). However, there is also evidence that the effect of intelligence on scholastic performance varies across different subjects. For example, Spinath et al. (2006) used a sample of German primary school students and reported that *g* was the strongest predictor in three subjects (*i.e.*, Mathematics, Science, and English), and even the only significant predictor in Science when compared to non-cognitive factors (*i.e.*, domain-specific self-perceived ability and intrinsic values). Lu et al. (2011) measured working memory as another cognitive predictor and found that it explained more variance in Math, while figural reasoning, as an indicator of Gf, explained more variance in Chinese in a sample of Chinese primary school students. Those authors also showed that the total amount of variance explained in Math was substantially larger than for Chinese. Consequently, the present study will include grades from different subjects as an indicator of Gf.

Personality and Scholastic Performance

Across different levels of education, personality has been shown to contribute independently to the prediction of academic performance above and beyond intelligence (Chamorro-Premuzic & Furnham, 2006; Chamorro-Premuzic & Furnham, 2008; Di Fabio & Busoni, 2007; Furnham & Chamorro-Premuzic, 2004; Furnham & Monsen, 2009; Heaven & Ciarrochi, 2012; Laidra et al., 2007; Noftle & Robins, 2007; Spinath et al., 2010; Steinmayr et al., 2011), which was summarized in recent meta-analyses (De Raad & Schouwenburg, 1996; O'Connor & Paunonen, 2007; Poropat, 2009; Richardson et al., 2012). Among the FFM domains, Conscientiousness is consistently identified as an important predictor of performance (Bratko et al., 2006; Laidra et al., 2007; O'Connor & Paunonen, 2007; Poropat, 2009; Richardson et al., 2012). Conscientiousness reflects a tendency to be purposeful, organized, reliable, determined, and ambitious (Digman, 1990), all of which are believed to be important for performance in work and academic settings (Barrick & Mount, 1991; Steinmayr & Spinath, 2008). After Conscientiousness, meta-analyses have shown that Openness also significantly predicted performance at the secondary and tertiary level ($\rho = 0.12$ and $\rho = 0.09$; Poropat, 2009; Richardson et al., 2012), which was often interpreted in terms of the positive correlation between Openness and intelligence. By contrast, the results of the relations between academic performance and the other three FFM domains are relatively weak or inconsistent. Agreeableness is characterized by altruism, cooperation, and trust (Digman, 1990). Meta-analyses indicate that Agreeableness had slightly lower correlations with performance at the secondary and tertiary level ($\rho = 0.05$ and $\rho = 0.06$; Poropat, 2009;

Richardson et al., 2012), which was interpreted in terms of cooperation within learning processes (De Raad & Schouwenburg, 1996). Neuroticism was reported to have a weak negative relation to scholastic performance (Bratko et al., 2006; Laidra et al., 2007; Steinmayr & Spinath, 2008), as neurotic students are thought to experience more negative affect and anxiety, reducing learning motivation (Major, Turner, & Fletcher, 2006) and impairing scholastic performance. However, other studies reported no or even positive effects (De Feyter, Caers, Vigna, & Berings, 2012; Komarraju, Karau, & Schmeck, 2009; Martin, Montgomery, & Saphian, 2006; Nguyen, Allen, & Fraccastoro, 2005). For Extraversion, a positive correlation with performance was reported in elementary school but became negative when kids grew older (Hogan & Hogan, 1995; Ziegler, Bensch, Maaß, Schult, Vogel, & Bühner, 2014; Ziegler, Danay, Schölmerich, & Bühner, 2010). This might be due to the two components of Extraversion: Ambition (referring to the need for dominance) and Sociability (referring to the need for affiliation). Especially the latter aspect of Extraversion may bring students to devoting time to socializing rather than studying.

Similar to what has been found for intelligence, relations between the FFM and scholastic performance were also subject-specific (Furnham & Monsen, 2009; Spinath et al., 2010). For instance, Neuroticism was found to predict grades in Math, Science, and foreign languages, but not in students' native language (Furnham & Monsen, 2009). Furthermore, Spinath et al. (2010) found that Conscientiousness and Neuroticism were important for Math achievement, but Extraversion was important for language achievement. It is important to note that these subject-specific effects might also explain some of the mixed results reported before.

Intelligence and the Domains of the FFM

A substantial body of literature has demonstrated complex relations between intelligence and personality (Chamorro-Premuzic, Von Stumm, & Furnham, 2015; Poropat, 2009; Richardson et al., 2012). Ackerman and Heggestad (1997) reported small-to-moderate correlations between intelligence and Openness to Experience ($\rho = 0.33$), Neuroticism ($\rho = -0.15$), and Extraversion ($\rho = 0.08$). Weaker correlations were reported with Conscientiousness ($\rho = 0.02$) and Agreeableness ($\rho = 0.01$). Another meta-analysis by Poropat (2009), only using student samples, found small correlations between the FFM and intelligence (*i.e.*, Agreeableness, $\rho = 0.01$; Conscientiousness, $\rho = 0.03$; Emotional Stability, $\rho = 0.06$; Extraversion, $\rho = -0.01$; Openness, $\rho = 0.15$). Because of these overlaps, it seems important to control for shared variance between the traits in order to identify specific effects. Surprisingly, very few studies have included both intelligence and personality measures to predict scholastic performance (Bratko et al., 2006; Di Fabio & Busoni, 2007; Furnham & Monsen, 2009; Heaven & Ciarrochi, 2012; Laidra et al., 2007). Besides focusing on the additive effects of intelligence and the FFM, other researchers proposed the idea of interaction effects between ability and personality.

Interaction Hypotheses

Very early, it was already proposed that performance might be determined by factors relating to the capacity to perform (*i.e.*, knowledge, skills, and intelligence), the opportunity to perform, which is affected by environmental constraints such as socioeconomic resources, and the willingness to perform (*i.e.*, motivation, cultural norms, and personality) (Blumberg & Pringle, 1982; Traag, van der Valk, van der Velden, de Vries, & Wolbers, 2005; also see Poropat, 2009). In other words, the willingness to perform does not automatically follow from the ability to perform. Thus, intelligence and personality variables might enhance or buffer their respective impact on scholastic performance. Zeidner (1995) contended that Conscientiousness might increase while Neuroticism might decrease the correlation between intelligence and performance. As mentioned, this general idea of an interaction between ability and personality can be traced back to early work performance models (Campbell, 1976; Heider, 1958; Maier, 1958; Mount, Barrick, & Strauss, 1999; Sackett, Gruys, & Ellingson, 1998), which state that job performance is an interactive function of motivation and ability. Denissen and Penke (2008) suggested that motivational reaction norms underlie the FFM. For Conscientiousness they hypothesized differences in the tenacity to pursue goals under difficult circumstances as the motivational root. This clearly reflects the notions by Zeidner (1995). Thus, based on the ideas by work psychologists and the theoretical assumptions by Denissen and Penke, it could be assumed that Conscientiousness enhances the impact of intelligence when predicting scholastic performance. This idea was supported in a study by Ziegler, Knogler, and Bühner (2009). Prior research also points to a specific interaction between Openness and intelligence. Ziegler et al. (2012) developed an integrative model of Openness, Gf, and Gc describing the complex interplay between those three traits. Those authors also found that Openness decreased the impact of fluid ability on grades that was used as a proxy for Gc. Unfortunately, no subject-specific analyses were conducted in either study. Moreover, the studies were conducted in a Western culture. Thus, the current study aimed at replicating the effects in a Chinese setting while also differentiating school subjects.

Aims of the Study

The aim of this study was to document the influences of Gf and the domains of the FFM on scholastic performance in a sample of Chinese secondary school students. Moreover, we extended previous research by focusing on interactive effects. Due to the practical and logistical limitations of a field study, we chose to measure figural reasoning as an indicator of Gf.

On the basis of the literature overview, we will test the following hypotheses:

Hypothesis 1: Effect of figural reasoning as an indicator of Gf on scholastic performance.

Controlling for other variables (FFM, possible interaction with FFM, age, gender), figural reasoning (as an indicator of Gf) is positively related to the performance in all three subjects (Chinese, Math, and English).

Hypothesis 2: Effect of the domains of the FFM.

Controlling for other variables (figural reasoning, possible interaction with figural reasoning, age, gender), the domains of the FFM are related to the performance in the three subjects. We expect a positive effect of Conscientiousness and Openness for all three subjects, of Extraversion for Chinese and English, and a negative effect of Neuroticism for Math and English.

Hypothesis 3: Moderation effects (interaction between figural reasoning and the domains of the FFM).

We expect that Conscientiousness has an enhancing effect and that Openness and Neuroticism have a buffering effect. Conscientiousness will make the effect of figural reasoning on performance stronger. If Openness is high, figural reasoning will not add much, and neither is figural reasoning expected to help when Neuroticism is high.

Method

Sample and Procedure

Students were surveyed at the beginning of their new semester (February 2013). A total of 836 Chinese secondary school students (girls = 406, M = 15.35, SD = 1.31 years) from grades 7 to 11 from five middle and high schools in the Fujian province took part in the study. Participants were offered detailed feedback as an incentive. All the assessments took place during regular class hours. Participants first had to provide some demographic information and then completed a figural reasoning test and a FFM questionnaire within two weeks. Midterm school grades in Math, Chinese, and English were collected from the teachers following the end of the courses three months later.

Measures

Scholastic Performance. Students' scholastic performance was based on the test scores from their midterm examinations in Math, Chinese, and English. Grades range from 0, the worst grade, to 150, the very best, with grades lower than 90 indicating insufficient performance. In the Chinese education system, midterm examinations are an important test for school students. All teachers teaching the same subject in the same grade of secondary school (usually three to four teachers) prepare test items according to what their students were supposed to have learned during the first half of the semester. The same teachers later correct and mark the tests. Importantly, the whole process is anonymous, i.e., teachers do not know which student they are grading. The contents that were tested differ across subjects: In Math, greater emphasis is placed on the processing of number information, application of arithmetic rules, and problem solving using arithmetic facts. In China, school textbooks in English are designed to teach grammar, vocabulary, and reading with less emphasis on listening, speaking, and writing. In addition, oral components are not manifested in the examinations at all, but are only part of regular class. In Chinese, teachers emphasize the mastering of grammar and sentence rules, as well as reading comprehension and writing.

Figural Reasoning. Raven's Standard Progressive Matrices (SPM; Raven, 1981) were used to assess students' figural reasoning as an indicator of Gf. This test is a measure of pure nonverbal reasoning ability, which is relatively independent of specific learning acquired in particular cultural or educational contexts (Jensen, 1998). The SPM comprises five sets (A to E) of 12 items each (*i.e.*, A1 to A12) with increasing difficulty across the items within a set. For each item, participants are asked to identify the missing element that completes a matrix from a number of options printed below (Raven, 1981). The test can be used across a wide age range. In the current study, the reliability estimate for the specified latent variable was McDonald's $\Omega_w = .97$ (Revelle & Zinbarg, 2009; Zinbary, Revelle, Yovel, & Li, 2005).

Domains of the FFM. The Chinese version of the NEO Five-Factor Inventory is a measure of 60 items assessing Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness (12 items per domain). Participants indicate the extent to which they agree or disagree with each item on a five-point scale ranging from 1 (*totally disagree*) to 5 (*totally agree*). In the current study, reliability estimates for the specified latent variables (Ω_w) were: 0.83 (Neuroticism), 0.81 (Extraversion), 0.67 (Openness), 0.63 (Agreeableness), and 0.82 (Conscientiousness), which is in line with other Chinese studies using the same scales (Yangang, Boxing, & Junqian, 2010; Yao & Liang, 2010).

Statistical Analyses

First, we computed zero-order correlations between all sum scores of the variables involved in this study using R (R Core Team, 2012). Second, to test **Hypotheses 1 to 3** for each of the three school subjects and for the composite of the three (Grade Composite), structural equation modeling was used. For the interaction hypotheses, an interaction effect was added based on latent moderated structural equations (LMS) as outlined by Klein and Moosbrugger (2000), which is more robust compared to ordinary least squares regressions. The latent variables corresponding to the five personality domains and to the three subjects are defined on the basis of item parcels, as will be explained. For the Grade Composite, the grades for Math, English, and Chinese were used as indicators. Third, we have also performed a regression analysis with ordinary least squares with the observed grade scores of the three subjects as dependent variables to double-check the results from the structural equation approach (SEM). Because the ordinary least squares results are very similar to the SEM results, only the latter will be reported (see Table A in Appendix).

All analyses were conducted in two steps. In step 1, figural reasoning, the FFM domains, age and gender were entered in the model. For the SEM analyses, figural reasoning and the FFM domains were latent variables, and for the ordinary least squares analyses, they were sum scores. In step 2, the interaction terms were added, following the latent moderator approach in case SEM was used. Because this SEM procedure has two steps, we use the term "hierarchical latent regression". For the ordinary least squares procedure, it is a regular hierarchical regression. This second step was repeated five times, for the interaction of each of the five personality domains with figural reasoning. It has to be noted that there are no regular fit indices available for the models containing latent interaction terms. Thus, these models were compared with the respective preceding model (*i.e.*, the one without the latent interaction term) using a Chi-square difference test (χ^2) based on log-likelihood values and scaling correction factors obtained with the robust maximum likelihood (MLR) estimator (Satorra & Bentler, 2001). In addition, the Bayesian Information Criterion (BIC) was used to compare nested models. All other models were evaluated based on the Comparative Fit Index (CFI), the Standardized Root Mean Square Residual (SRMR), and the Root Mean Square Error of Approximation (RMSEA) with a 90% confidence interval (Beauducel & Wittmann, 2005; Hu & Bentler, 1998, 1999; Marsh & Hau, 2004; Maydeu-Olivares & McArdle, 2005). We deemed the fit to be acceptable with cut-offs of CFI $\geq$ 0.90, RMSEA $\leq$ 0.08, and SRMR $\leq$ 0.06 (see also Heene, Hilbert, Draxler, Ziegler, & Bühner, 2011). Models with lower BIC values are expected to be more parsimonious and better-fitting when compared with other nested models (Klein, 2011). We applied full information maximum likelihood estimation (FIML) to deal with missing values (Rubin &Little, 2002). In addition, a robust estimator was used to deal with violations of the multivariate normal distribution (MLR), along with academic level as a stratification variable to correct for the nested data structure due to different academic levels. Standardized regression coefficients are not provided by Mplus

(Muthén & Muthén, 1998 - 2012) for LMS models. Following the suggestion by Klein and Moosbrugger (2000), standardized beta coefficients were obtained by standardizing the data prior to analyses. Finally, for the latent moderation models from step 2, a procedure outlined by Preacher, Curran, and Bauer (2006) was used to obtain interaction plots if the moderation effect was significant. Thus, specific values for the (centered) moderator were entered into a regression equation to assess the effect of figural reasoning on school grades at specific conditional values of the moderator (*i.e.*, the mean, 1 *SD* above and 1 *SD* below the mean; see Preacher, Curran, & Bauer, 2003).

In order to define latent variables for figural reasoning and the FFM, we first tested measurement models. Each of the latent variables was represented by three parcels (Little, Rhemtulla, Gibson, & Schoemann, 2013). In order to construct the parcels, we conducted a series of single factor analyses for each latent construct except for figural reasoning. When parceling the items for the FFM domains, we allocated each of the three items with the highest loadings to one parcel. The next three highest-loading items were allocated likewise but in a reverse order starting with parcel 3 and so on. Using these three parcels as indicators of a latent variable yields a just-identified model. Such models have zero degrees of freedom and thus, by definition, a perfect model fit: CFI = 1.00, RMSEA = 0.00, SRMR = 0.00. According to Brown (2006), such models can still be evaluated in terms of the interpretability and strength of their parameter estimates. As for figural reasoning, three parcels were built representing the three factors underlying the SPM suggested by Lynn, Allik, and Irwing (2004). Our results showed that factor loadings in all measurement models were significant ($p < 0.001$), ranging from 0.23 to 0.59 [1].

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[1] In order to decide whether an item parcel loaded appropriately on its respective factor, we used a cut-off of 0.40 for standardized factor loadings (Tabachnick & Fidell, 2001). In our study, most of the standardized factor loadings were close to or larger than 0.40, except for some indicators of Openness and Agreeableness that were slightly lower than 0.40.

Results

Missing Data Analysis

A significant Little's Missing Completely at Random test, χ^2 (144) = 252.60, $p < 0.05$, indicated our missing data were not missing completely at random (Little, 1988). However, as recommend by Schafer and Graham (2002), multiple imputation or FIML are preferable to deal with missing data compared to casewise or listwise deletion with less than 5% missing data, which was the case here. It is also important to note that participants who had missing data did not differ significantly from those who had no missing data along any of the variables under study. Therefore, we decided to use FIML to deal with missing data.

Correlational Analyses

Descriptive statistics, reliability estimates, and zero-order correlations between all sum scores are reported in Table 1. As can be seen, figural reasoning was most strongly associated with Math and English grades but only had a small correlation with Chinese grades. Regarding the FFM domains, Conscientiousness and Openness displayed significant and small-to-moderate correlations with Math, Chinese, and English grades. Neuroticism was negatively associated with Math grades only, whereas Extraversion was positively associated with Chinese grades only. Gender and age displayed small-to-medium correlations with figural reasoning, personality, and school grades in Math, Chinese, and English.

Latent Moderated Structural Equation Modeling

Table 2 shows acceptable model fits for all models, and Table 3 shows the estimates for the analyses without and with the moderator effect. Because the moderation was only significant for Openness, only the estimates for the models with a moderator effect of Openness are shown.

Hypothesis 1 was supported in all models. Thus, figural reasoning predicted performance for all grades and for the composite. **Hypothesis 2** was confirmed for Openness.

Openness had a positive effect on performance for all subjects. For Conscientiousness, the effects were clearly smaller and, at the .05 level, only significant for Math in both steps. For Extraversion, the results do not support the research hypothesis. All estimated effects for this domain are very small and not significant. Finally, Neuroticism had a negative effect on Math performance but not on English performance.

Finally, **Hypothesis 3** was confirmed for Openness but not for Conscientiousness and Neuroticism. All interactions with Openness were significant and Figure 1 shows that, as expected, figural reasoning had positive effects if Openness was low but not if it was high. A high degree of Openness is a buffer against lower fluid intelligence as far as was measured through figural reasoning.

Table 1. Descriptive statistics and zero-order correlations between sum scores of all variables studied.

Variables	**Bivariate correlations**											**Descriptive statistics**	
	1	2	3	4	5	6	7	8	9			*M*	*SD*
1. Gender	---											1.52	0.50
2. Age	0.01	---										15.35	1.51
3. Figural reasoning	< 0.01	0.14 **	(**0.97**)									46.85	12.15
4. Neuroticism	0.14 **	0.17 **	< 0.01	(**0.83**)								35.28	7.76
5. Extraversion	0.03	−0.12 **	0.01	−0.37 ***	(**0.81**)							42.49	6.60
6. Openness	0.02	0.10 *	0.09 *	−0.03	0.14 **	(**0.67**)						41.78	5.70
7. Agreeableness	0.01	0.10 *	−0.01	0.38 ***	−0.16 **	−0.07	(**0.63**)					29.03	5.16
8. Conscientiousness	0.07 *	−0.08 *	−0.03	−0.41 ***	0.16 **	0.20 ***	−0.30 ***	(**0.82**)				38.34	6.30
9. Math grades	−0.06	0.07	0.31 ***	−0.12 **	0.05	0.21 ***	−0.04	0.13 **	---			96.47	33.10
10. Chinese grades	0.23 **	−0.13 **	0.11 **	−0.07	0.13 **	0.18 ***	−0.09 *	0.14 **	0.54 ***	---		97.52	19.19
11. English grades	0.13 **	0.14 **	0.31 ***	−0.03	0.06	0.28 ***	−0.01	0.11 *	0.67 ***	0.61 ***	---	98.07	32.56

Note. N = 686 to 836. Reliability estimates for each variable (Ω_w) are in parentheses on the diagonal. Gender: 1 = men and 2 = women. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. All p-values are two-tailed.

Table 2. Model fits.

School subject	**Model**	**χ^2 (*df*)**	**RMSEA [90% CI]**	**CFI**	**SRMR**	**BIC**	**Chi-square Difference Test (TRd)**
Grade Composite	Step 1	817.32 (208)	0.059 [0.055,0 .063]	0.920	0.057	40731.53	
	Step 2	**---**	**---**	**---**	**---**	**40706.37**	$\Delta\chi^2$ (*df*) = 9.69 (1), $p < 0.001$
Chinese	Step 1	614.72 (168)	0.056 [0.052, 0.061]	0.933	0.054	27303.51	
	Step 2	**---**	**---**	**---**	**---**	**27289.58**	$\Delta\chi^2$ (*df*) = 6.27 (1), $p < 0.05$
Math	Step 1	632.28 (168)	0.057 [0.053, 0.062]	0.931	0.055	28100.34	
	Step 2	**---**	**---**	**---**	**---**	**28085.67**	$\Delta\chi^2$ (*df*) = 11.87 (1), $p < 0.001$
English	Step 1	638.98 (168)	0.058 [0.053, 0.063]	0.930	0.055	28055.25	
	Step 2	**---**	**---**	**---**	**---**	**28041.59**	$\Delta\chi^2$ (*df*) = 11.03 (1), $p < 0.001$

Note. N = 836. The model showing the best fit in each school subject is in bold. Because traditional model fit indices are not developed for latent moderated structural equation (LMS) models, we used a Chi-square difference test based on log-likelihood values and scaling correction factors obtained by the robust maximum likelihood (MLR) estimator to compare the relative fit of Step 1 and Step 2: Satorra-Bentler scaled chi-square difference test (TRd) = −2 * (L0–L1)/[(p0 * c0–p1 * c1)/(p0–p1)] where L0 and L1 are the log-likelihood values for Step 1 and Step 2, respectively, as well as scaling correction factors c0 and c1 for Step 1 and Step 2, respectively. p0 and p1 are the number of parameters in Step 1 and Step 2, respectively.

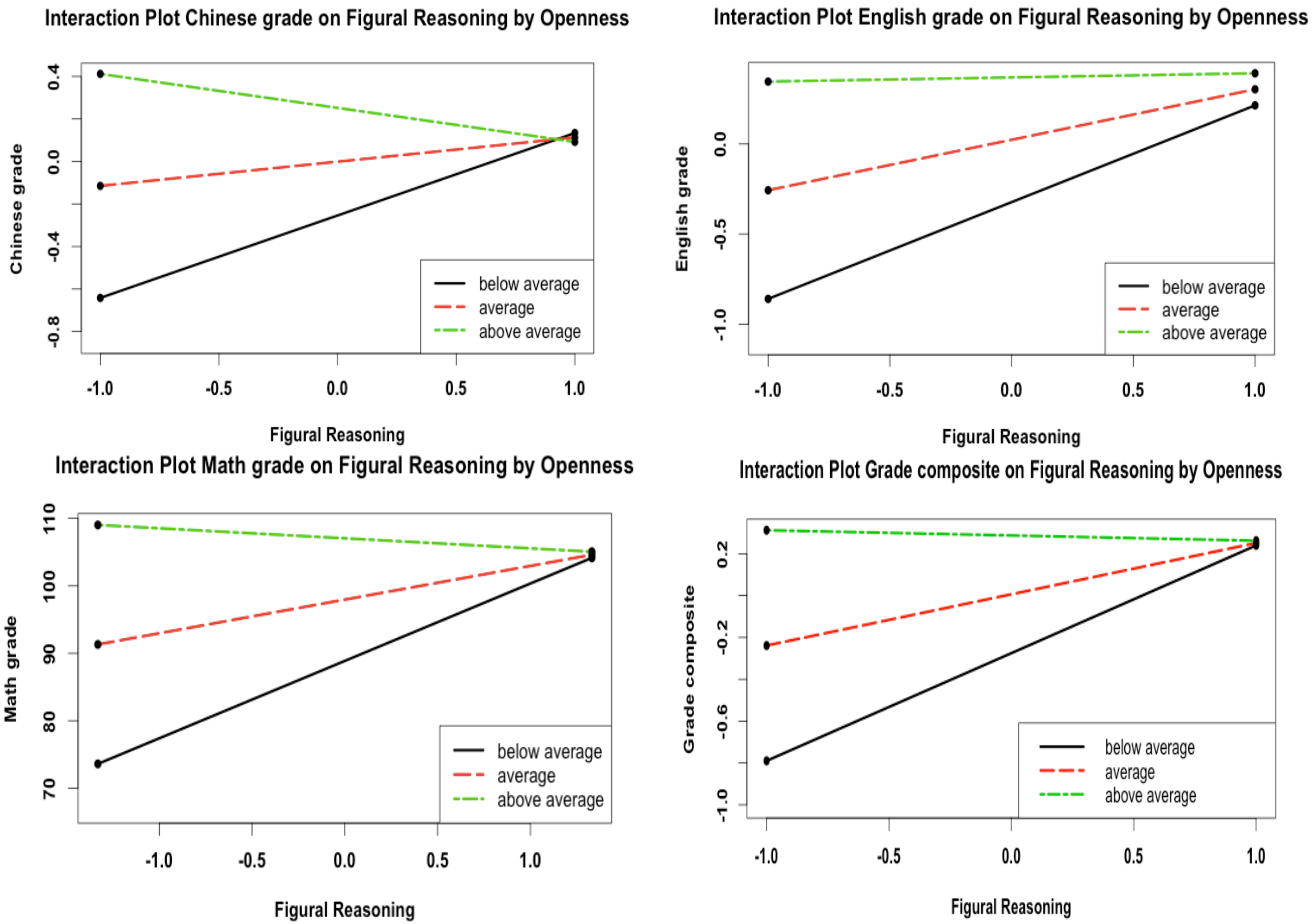

Figure 1. Interaction plots for the moderating effect of Openness on the correlation between figural reasoning and school grades in Chinese, Math, English, and a grade composite.

Table 3. Prediction of scholastic performance in Chinese, Math, and English: results from hierarchical latent regression models.

Enter variables	Chinese grade			Math grade			English grade			Grade Composite		
	ß	R^2	ΔR^2	ß	R^2	ΔR^2	ß	R^2	ΔR^2	ß	R^2	ΔR^2
Step 1		0.15 ***	0.05 *		0.17 ***	0.08 **		0.21 ***	0.10 ***		0.25 ***	0.12 ***
Gender	0.23 ***			−0.05			0.13 ***			0.13 **		
Age	−0.14 **			0.04			0.10 **			0.06		
Figural reasoning	0.12 **			0.29 ***			0.26 ***			0.29 ***		
Neuroticism	−0.03			−0.12 *			−0.08			−0.09		
Extraversion	0.04			−0.02			−0.02			−0.01		
Openness	0.19 ***			0.23 ***			0.31 ***			0.33 ***		
Agreeableness	−0.02			0.11			0.09			0.09		
Conscientiousness	0.05			0.12 *			0.07			0.09 *		
Step 2		0.22 ***	0.07 **		0.24 ***	0.07 **		0.25 ***	0.04 *		0.36 ***	0.11 ***
Gender	0.22 ***			−0.05			0.13 ***			0.09 **		
Age	−0.15 ***			0.01			0.09 *			0.02		
Figural reasoning	0.12 **			0.31 ***			0.28 ***			0.25 ***		
Neuroticism	−0.04			−0.13 *			−0.08			−0.08 #		
Extraversion	0.03			−0.03			−0.03			−0.02		
Openness	0.25 ***			0.28 ***			0.35 ***			0.28 ***		
Agreeableness	0.01			0.14 *			0.11 #			0.09 #		
Conscientiousness	0.06			0.13 *			0.08 #			0.08 #		
Figural reasoning *Openness	−0.27 ***			−0.28 ***			−0.26 ***			−0.27 ***		

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; # $p < 0.10$. All p-values are two-tailed.

Discussion

This study aimed at evaluating the specific contributions of figural reasoning as an indicator of Gf, the domains of the FFM, and their interaction in predicting scholastic performance in Chinese secondary school students. Generally speaking, our findings replicated the specific effects for Gf and some of the personality domains on scholastic performance found in Western cultures in an Eastern culture. In addition, our findings further supported the idea that Gf and Openness interacted with each other in predicting scholastic performance across three subjects.

Fluid Intelligence

Although the positive relationship with all grades turned out to be clearly positive for all subjects, the effect was smaller for Chinese. This smaller effect is in line with earlier results (McGrew, 2008; Taub et al., 2008) and may be due to how students learn Chinese in comparison with other subjects. Because the other subjects are new (Math, English) they may require more Gf than is the case for the native language. Mathematics requires the students to solve new and difficult problems, and English places heavy demands on learning a new grammar and a new vocabulary. In contrast, people learn their native language through everyday interactions and what they have to learn has a higher degree of familiarity. This may explain why there is less variation in proficiency for Chinese than for Math and English (see Table 1). On the whole, the total amount of variance explained by figural reasoning as an indicator of Gf in school grades, especially in Chinese (native language), was smaller than reported in Western cultures (Heaven & Ciarrochi, 2012; Spinath et al., 2006). We attribute this difference mainly to Chinese culture. Adopting Confucian doctrines, Chinese parents and teachers might encourage their children and students to compensate for limitations in abilities with Conscientiousness and hard work (Tweed & Lehman, 2002). Thus, such cultural differences might produce mean level differences and also influence the relative importance of variables in predicting scholastic performance (Lu et al., 2011). Another explanation could be that within the field of intelligence research, very elaborate models have been developed, including different intelligence facets: verbal, numerical, and figural reasoning abilities (Beauducel, Brocke, & Liepmann, 2001). According to Brunswik's lens model (Wittmann & Süß, 1999), symmetry between predictor and criterion could increase correlations (see also Ziegler et al., 2010; Ziegler, Dietl, Danay, Vogel, & Bühner, 2011). Future studies should therefore strive to apply broad measures of Gf in Chinese contexts. In fact, another study conducted in China found stronger test criterion correlations for Gf using a broader cognitive test battery in a sample of elementary school students (Lu et al., 2011).

Domains of the FFM

In line with prior research (Poropat, 2009), Openness was found to be a significant and positive predictor for performance in all three subjects. Further, Conscientiousness was a positive predictor and Neuroticism a negative predictor of performance in Math. Conscientious students are more likely to perform well academically because they are more likely to be achievement-oriented, organized, responsible, and willing to work hard. Our findings that Neuroticism is a negative predictor are consistent with Spinath et al. (2010), who suggested that the negative effect of Neuroticism on Math grades might be due to anxiety. Mathematics is associated with challenges, exam stress, and problem solving, all of which might spark anxiety, leading to a decrease in performance.

Moderation

The results support the interaction hypothesis for Openness and Gf. Specifically, the effect each of the traits is smaller the higher the score of the other is. Though the moderation found here was reported before (Ziegler et al., 2012), no conclusive explanation was provided. Now that the moderation has been replicated in an independent sample and a different culture, concrete hypotheses regarding the nature of the mechanism at work are justified. Formally speaking, the negative interaction between Openness and figural reasoning can be interpreted as a disjunctive or compensatory relationship: one of both traits is sufficient to perform well, so the fact that the other trait does not add to the variance explained when one trait is already high. This means that students high in Gf are able to handle school tasks even when they are not curious or seeking new knowledge. Similarly, students high in Openness may not need strong fluid intelligence because they are curious about different fields, actively grasping new ideas and seeking novel experiences. Another possible explanation is that a high intelligence combined with a high openness is not necessarily beneficial in a school context. A high intelligence combined with lots of imagination and curiosity might lead to distraction and low interest in the contents taught in schools. For a student with lower intelligence and a high openness the contents may satisfy the high level of curiosity, and for a student with a high intelligence and a low level of openness the school contents would be sufficient as a challenge. Future research could apply experimental methods or experience sampling to gather more data to help test these different ideas.

However, our results failed to support the enhancing effect of Conscientiousness, so the results of Ziegler et al. (2009) could not be confirmed. Whereas the present study only employed short tests, Ziegler et al. (2009) used a faceted intelligence measure and a broad personality questionnaire. Thus, future studies trying to replicate this specific interaction in a Chinese context should also employ such broad measures. The same argument holds regarding the other interaction effects which were insignificant in this study.

Limitations of the Current Study

The use of a short personality inventory and a figural reasoning test as an indicator of Gf limits the findings to the tests used. Broader and, most importantly, faceted measures are needed to provide a more comprehensive answer to the research questions posed above.

Second, our findings rely on self-reported data. Prior research has shown that other reports are incremental predictors of academic performance above and beyond intelligence (Ziegler et al., 2010) and self-reports (Poropat, 2014). The sole reliance on self-reports should be opened up in future studies by using other reports as well. Finally, using grades as dependent variables might be considered a limitation. Despite the importance of grades in students' lives, aspects other than actual performance differences affect grades, which therefore can be considered contaminated (Brogden & Taylor, 1950; Ziegler & Brunner, in press). Using more objective criteria like standardized assessments will most likely increase the predictive power of ability.

Conclusions

The current study confirmed the influences of Gf-type test performance and the FFM domains on scholastic performance within the Chinese culture. In general, a higher Gf leads to better scholastic performance. However, it does not follow that intelligence is the only determinant of scholastic performance. Clearly, personality traits, particularly Openness, can be used along with Gf to better predict scholastic performance. Moreover, this study also emphasizes the importance of considering specific subjects when predicting scholastic performance (*i.e.*, Chinese, English, and Math). More importantly, this study further indicated that Openness moderated the effects of Gf on scholastic performance in three subjects. Chinese teachers and parents may want to stimulate the students' Openness because of its positive contribution to scholastic achievement, especially when fluid intelligence is not so high.

Appendix

Table A. Prediction of scholastic performance in Chinese, Math, and English: results from hierarchical regression analyses.

Enter variables	Chinese grade			Math grade			English grade		
	ß	R^2	ΔR^2	**ß**	R^2	ΔR^2	**ß**	R^2	ΔR^2
Step 1		0.15 ***			0.16 ***			0.18 ***	
Gender	0.20 ***			−0.05			0.14 ***		
Age	−0.21 ***			−0.02			0.06 #		
Figural reasoning	0.14 **			0.31 ***			0.28 ***		
Neuroticism	−0.01			−0.06			−0.02		
Extraversion	0.05			0.01			−0.01		
Openness	0.15 ***			0.16 ***			0.23 ***		
Agreeableness	−0.05			0.03			0.03		
Conscientiousness	0.07 #			0.11 **			0.08 *		
Step 2		0.17 ***	0.02 *		0.18 ***	0.02 *		0.20 ***	0.02 *
Gender	0.20 ***			−0.05			0.14 ***		
Age	−0.22 ***			−0.02			0.05		
Figural reasoning	0.12 **			0.29 ***			0.27 ***		
Neuroticism	−0.01			−0.06			−0.03		
Extraversion	0.05			0.01			−0.01		
Openness	0.16 ***			0.17 ***			0.23 ***		
Agreeableness	−0.05			0.03			0.03		
Conscientiousness	0.08 #			0.12 **			0.09 *		
Figural reasoning * Openness	−.016 ***			−0.17 ***			−0.16 ***		

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; # $p < 0.10$. All p-values are two-tailed.

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How do the Big Five influence Scholastic Performance? A Big Five-Narrow Traits Model or A Double Mediation Model

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Abstract: The current study develops the Big Five-Narrow Traits Model [B5NT] suggesting a general mechanism by which the Big Five affect scholastic performance. Moreover, the B5NT is compared to the Double Mediation Model that was also suggested to explain said mechanism. In both models self-beliefs (i.e., subject-specific self-efficacy and subject-specific self-concept) and learning approaches are seen as relevant mediators, but are sequenced differently. Data were collected from 836 Chinese secondary school students. The results strongly support the B5NT. Across three subjects (Math, Chinese, English), subject-specific self-concept significantly mediated the influences of Openness and Conscientiousness on grades while a surface-learning approach mediated the influences of Openness, Extraversion, and Neuroticism. A deep-learning approach also significantly mediated the relations of Openness and Conscientiousness with grades but only in Math and Chinese. In addition, Neuroticism also influenced Math grades via Math self-concept. Agreeableness did not predict grades directly or indirectly. Implications are discussed, along with limitations and suggestions for future research.

Keywords: Big Five-Narrow Traits model, Double Mediation model, self-beliefs, learning approaches, scholastic performance

A wide range of cognitive, personality, and other narrower traits contribute to scholastic performance (e.g., Bong & Skaalvik, 2003; Kuncel, Hezlett, & One, 2004; Marsh & Craven, 2006). Meta-analyses have shown that personality traits based on the Five-Factor Model, in particular Openness and Conscientiousness contribute to the prediction of scholastic success above and beyond intelligence (Poropat, 2009; Richardson, Abraham, & Bond, 2012). However, the underlying processes are still unclear. Additionally, prior studies have mostly been conducted in Western culture, little is known about these effects in non-Western cultures. Previous intercultural research indicated that Asian students perform better in school than their Western peers, especially in Math and Science (Harmon et al., 1997). Several explanations for this have been proposed: compared to Western students, Asian students possess higher academic motivation in that they believe in learning through effort rather than innate ability (Dweck, & Molden, 2000; Tong, Zhao, & Yang, 1985; Tweed & Lehman, 2002). Asian parents have higher expectations and get more involved in their children's learning than Western parents (Stevenson & Stigler, 1992; Yao, 1985). Considering these differences, it is reasonable to assume that the predictive power of personality traits and the specific mechanisms derived from studies in Western cultures do not necessarily replicate in Chinese samples. Consequently, the present study aimed at introducing a new theoretical model suggesting mechanisms by which the Big Five affect scholastic performance. Moreover, this model was tested against an already existing theoretical model using data gathered in China.

Personality and Scholastic Performance

Since the wide acceptance of the Big Five (i.e., Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness; Goldberg, 1992), a series of meta-analyses on the relation between those traits and scholastic performance were conducted. Conscientiousness was the most powerful predictor across the secondary and tertiary levels (ρ = .21 & 23:

Poropat, 2009; ρ = .23: Richardson et al., 2012). Conscientiousness reflects a tendency to be purposeful, organized, reliable, determined, and ambitious (Digman, 1990). After Conscientiousness, Openness is the personality trait with the strongest correlations with performance at the secondary and tertiary levels (ρ = .12 & .09: Poropat, 2009; ρ = .09: Richardson et al., 2012). Students high in Openness are expected to be curious about new and challenging materials and to be imaginative (Digman, 1990). In doing so, they acquire a large knowledge base (Ziegler, Danay, Heene, Asendorpf, & Bühner, 2012). Agreeableness is characterized by being altruistic, cooperative, and trusting (Digman, 1990). Agreeableness had slightly lower meta-analytic correlations with performance at the secondary and tertiary levels (ρ = .05 & .06: Poropat, 2009; ρ = .07: Richardson et al., 2012). Students high in Agreeableness may attend classes consistently (Lounsbury, Sundstrom, Loveland, & Gibson, 2003) and show greater levels of cooperation with teachers, which could facilitate learning processes (Vermetten, Lodewijks, & Vermunt, 2001). By contrast, students high in Neuroticism tend to be anxious, depressed and hostile (Digman, 1990). These students are expected to experience higher levels of anxiety and pay more attention to their emotional states, thereby potentially impairing performance. No significant correlations between Neuroticism and lower performance at the secondary and higher levels of education were found (ρ = .01 & -.01: Poropat, 2009; ρ = -.01: Richardson et al., 2012). Extraversion reflects a tendency to like people, prefer being in large groups, and desire excitement and stimulation (Digman, 1990). Students high in Extraversion are expected to participate in social activities rather than studying, which leads to academic failure (De Raad & Schouwenburg, 1996). Only very small correlations at the secondary and tertiary levels were reported (ρ = -.03 & -.01: Poropat, 2009; ρ = -.03: Richardson et al., 2012).

Moreover, for adolescents relations between the Big Five and scholastic performance seem to be subject-specific. For example, Conscientiousness and Neuroticism were found to be important for Math but Extraversion to be important for language learning (Spinath, Freudenthaler, & Neubauer, 2010). Furthermore, it has been found that Neuroticism is predictive of Math grades, Science grades, and foreign language grades but not native language grades (Furnham & Monsen, 2009).

Personality and Learning Approaches

Previous studies have documented that students' personality traits influence learning approaches and subsequent learning outcomes (Chamorro-Premuzic & Furnham, 2009). Biggs, Kember, and Leung (2001) differentiated a deep-learning approach, which involves seeking a real understanding of what is learnt and a surface-learning approach, which involves seeking only a reproduction of what is taught to meet minimum requirements. Zhang's (2003) study with Chinese students found that Conscientiousness and Openness positively predicted deep-learning approaches, whereas Neuroticism positively predicted surface-learning approaches. Duff, Boyle, Dunleavy, and Ferguson (2004) further indicated that deep-learning approaches were positively associated with Extraversion and Openness to experience, whereas surface-learning approaches were positively associated with Neuroticism and Agreeableness.

Importantly, learning approaches were found to influence scholastic performance (Furnham et al., 2009; Watkins, 2001; Wong & Watkins, 1998). It is suggested that those who use deep-learning approaches get higher grades, while those who learn by means of surface-learning approaches obtain lower grades. Other researchers argued that students' personality traits might influence scholastic performance indirectly through learning approaches. Diseth (2003) found that Openness exerted its influences on achievement through deep-learning approaches. In line with this, Shokri, Kadivar, Valizadeh, and Sangari (2007) showed that the effects of Openness and Conscientiousness on academic performance were positively mediated by deep-learning approaches but negatively by surface-learning approaches. In addition, Neuroticism also influences performance positively and indirectly via surface-learning approaches (see also Swanberg & Martinsen, 2010). Thus, there is empirical evidence linking the Big Five, learning approaches, and scholastic performance.

Personality, Self-beliefs, and Learning Approaches

A large body of research has revealed self-beliefs including academic self-efficacy and academic self-concept to be important for students' learning (Bong & Skaalvik, 2003; Lee, 2009). Academic self-efficacy refers to students' beliefs about their abilities to successfully perform their class work (Bong & Skaalvik, 2003) or to master specific academic subjects (Pastorelli et al., 2001). In the academic domain, self-efficacy was found to be a good predictor of deep-learning approaches and scholastic performance (Bandura, 1993; Lee, Lee, & Bong, 2014; Zimmerman, 2000). Bandura argued that students with high self-efficacy appear to put more effort and persistence into specific scholastic tasks, use more deep-learning approaches, and ultimately attain their scholastic success. In addition, subject-specific self-efficacy also exerts the strongest effect on performance (Chen & Zimmerman, 2007). However, few studies have investigated the effects of subject-specific self-efficacy on specific scholastic performance, and such studies have often emphasized only Math self-efficacy (Morony, Kleitman, Lee, & Stankov, 2013).

Likewise, academic self-concept[2], which refers to individuals' knowledge and perceptions about themselves in academic setting (Wigfield & Karpathian, 1991), was found to predict deep-learning approaches and scholastic performance. Drew and Watkins (1998) showed that academic self-concept affected learning approaches that students adopted and

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[2] Academic self-concept appears to differ from academic self-efficacy pertaining to the level of specificity. Academic self-efficacy questionnaires most often refer to specific tasks, whereas academic self-efficacy questionnaires typically refer to specific school subjects (Bong & Skaalvik, 2003). However, some researchers argued that the primary reason for assessing self-efficacy at different levels of specificity is to ensure correspondence between self-efficacy and performance criteria. When predicting performance of broader scope such as course grades and overall grade point averages, self-efficacy at correspondingly broader levels should be assessed (Pajares & Miller, 1995; Randhawa, Beamer, & Lundberg, 1993; Zimmerman et al., 1992).

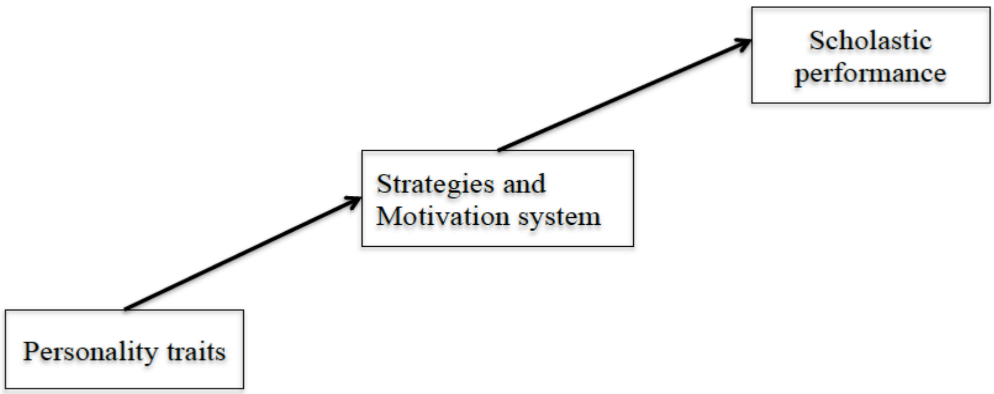
subsequently influenced achievement outcomes. Moreover, not only does there appear to be a strong association between academic self-concept and scholastic performance, but this relation appears to be domain-specific: Self-concept in one domain (i.e., Math self-concept) is more strongly associated with performance in that domain (i.e., Math grade) than in other domains (Marsh & Seaton, 2012).

In addition, several researchers also found significant relations between students' personality traits and self-beliefs. For example, Conscientiousness and Openness were positively related to academic self-efficacy (Peterson & Whiteman, 2007), whereas Neuroticism was negatively related to academic self-efficacy (Judge & Ilies, 2002). Shams, Mooghali, and Soleimanpour (2011) further indicated that the effects of Openness and Agreeableness on Math performance were mediated by self-efficacy. Similarly, Marsh and Craven (2006) showed that self-concept facets correlated strongest with Neuroticism (r = -.82) and Extraversion (r = .71), but were nearly uncorrelated with Agreeableness. Conscientiousness was positively related to Math self-concept, and Openness was substantially correlated with verbal self-concept (r = .49) but negatively correlated with Math self-concept (r = -.12). A longitudinal study by Hair and Graziano (2003) further demonstrated that Openness and Agreeableness exerted their influences on scholastic performance indirectly through scholastic self-esteem (a proxy for scholastic self-concept).

Summarizing, previous studies have established that the Big Five, self-beliefs and learning approaches are all interrelated and are likely to influence scholastic performance. It seems that these factors do not operate separately but form a complex network that brings about changes in performance.

Integrative Theories

McAdams (1995) proposed an analysis model of personality, which was extended by Graziano, Jensen-Campbell, and Finch (1997), suggesting that individual differences in personality can be described at three levels (see Figure 1). Level 1 comprises relatively unconditional, decontextualized personality dimensions that refer to what a person " has." Level 2 consists of contextualized strategies and plans that enable people to solve tasks and meet their goals and thus refers to what a person "does." Level 3 is the domain of the life narrative, in which people construct stories about their lives to provide a sense of overall meaning to their lives. In this regard, the Big Five personality traits belong to Level 1 and narrow traits (i.e., self-beliefs and learning approaches) belong to Level 2. It is likely that Big Five exerted their influences on scholastic performance through the ways people use self-beliefs and strategies system. Similarly, Asendorpf and van Aken (2003) called the Big Five *core personality traits* and self-concept surface *characteristics*. It can be assumed that the influences of core personality traits on scholastic performance are likely to be mediated, at least in part through surface traits.



	Levels of analysis	
Level 1	**Level 2**	**Level 3**
decontextualized comparative dispositions	situated strategies ; goal-directed activities	reflective descriptions; retrospective, schematic life stories as narratives

Figure 1. The Levels of Analysis Model (Graziano, Jensen-Campbell, & Finch, 1997).

Although the abovementioned theoretical approaches emphasized the mediating roles of narrow traits, very few studies actually tested this idea (Corker, Oswald, & Donnellan, 2012; Diseth, 2003; Hair & Graziano, 2003; Richardson & Abraham, 2009; Shams et al., 2011; Shokri et al., 2007; Swanberg & Martinsen, 2010). Moreover, none of the previous studies has addressed several potential core traits simultaneously, therefore the relations among them and more importantly the specific processes by which they affect scholastic performance remain unclear, as the overlap between the variables is not fully controlled for. In addition, prior studies did not consider subject specificity of some traits when exploring the underlying processes. The conclusions regarding the specificity of the reported indirect effects are therefore premature, especially considering the overlap among the narrow traits. Consequently, a Big Five-Narrow Traits model (B5NT, see Figure 2) was proposed in which the influence of the Big Five on scholastic performance went through subject-specific self-beliefs and learning approaches.

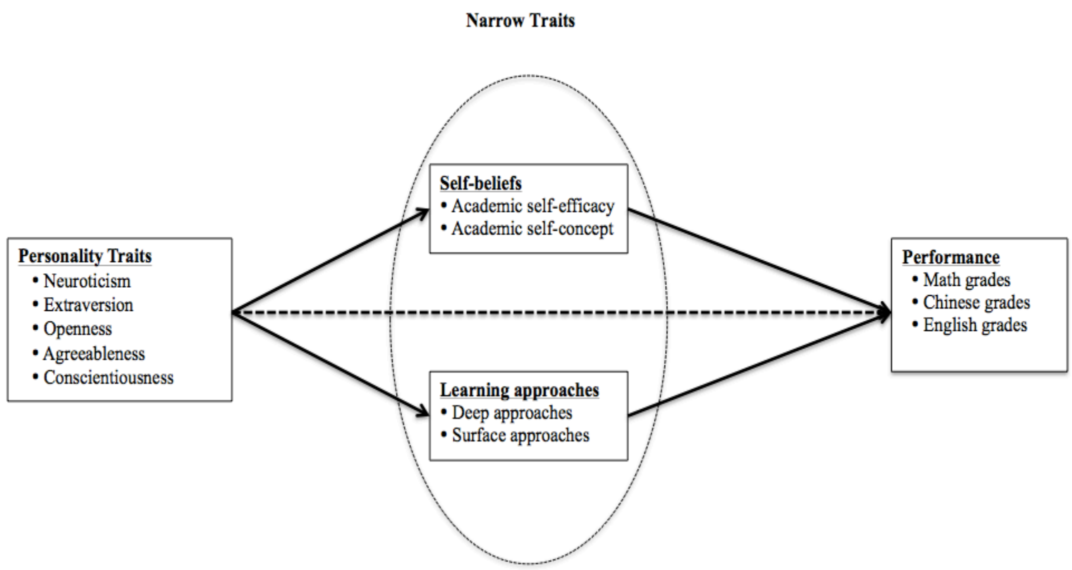


Figure 2. The Big Five-Narrow Traits model. *Note.* The model includes paths from the Big Five to self-beliefs and learning approaches. Moreover, all domains of the Big Five influence school grade in Mathematics, Chinese, and English simultaneously via self-beliefs and learning approaches. Dashed lined arrows specify direct effects.

Mumford and Gustafson (1988) proposed a model that can be seen as an alternative. They proposed that the Big Five provided the motivational impulses or the motivational blocks to use or not to use learning strategies and thus to improve or turn down performance. This idea specifies a double mediation effect in the relations between the Big Five and scholastic performance (see Figure 3 for this Double Mediation [DM] model). A longitudinal study by Corker et al. (2012) focusing on Conscientiousness provided initial evidence for the DM model (i.e., Conscientiousness → Mastery approach → effort strategies → exam performance). Unfortunately, only one Big Five domain was measured and the specific processes for different subjects were not analyzed.

Clearly, conceptually both models make strongly differing assumptions regarding the actual process taking place. Whereas the DM model sees the role of the Big Five only in terms of motivation, the B5NT model gives the Big Five a broader role, affecting motivation and strategy at the same time.

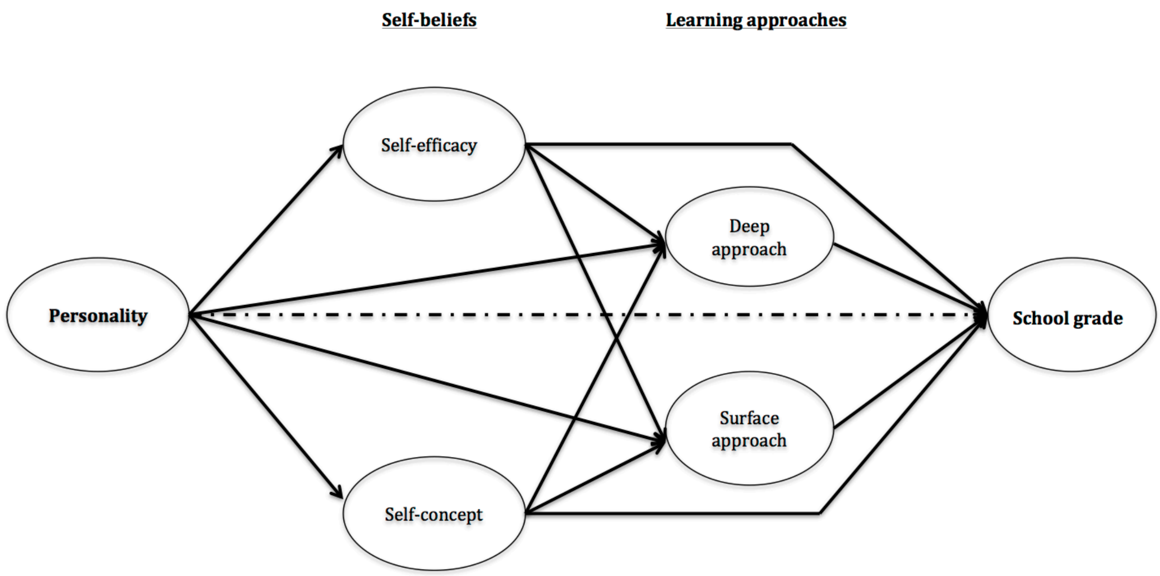


Figure 3. Double Mediation model. *Note.* The Big Five predict school grades in Mathematics, Chinese, and English directly and indirectly via self-beliefs and learning approaches. In addition, the Big Five influence learning approaches directly and indirectly via self-beliefs. Self-beliefs predict school grades directly and indirectly via learning approaches.

Purpose of Present Study

Two alternative process models from the Big Five to scholastic performance can be proposed based on the current literature and are being compared here. The B5NT model assumes simultaneous indirect effects of the Big Five through self-beliefs and learning approaches. The alternative DM model assumes that the Big Five influence self-beliefs, which in turn activate specific learning approaches affecting scholastic performance. Based on prior findings, subject-specific self-beliefs and learning approaches were conceptualized as potential mediators for both models. Furthermore, as much of the prior research focusing on the relations between the Big Five, self-beliefs, learning approaches, and scholastic performance was conducted in Western cultures, the current study will replicate and extend prior findings by using data gathered in China.

Method

Sample and Procedure

A total of 836 secondary school students from grades 7 to 11 from the Fujian province of China participated voluntarily and received feedback on their results. Table 1 provides an overview of the number of participants at each grade as well as their mean age and gender distribution. Data were collected during the first 2 weeks of the academic semester (February 2013) during regular class hours. Course grades were collected from the teachers after the courses ended three months later.

Table 1. Demographic Variables

Sample	*N*	Age	Boys (*N*)	Girls (*N*)
Grade 7	104	M = 13.81, SD = .83	53	51
Grade 8	275	M = 14.41, SD = .81	131	144
Grade 10	412	M = 16.19, SD = .73	198	214
Grade 11	27	M = 17.41, SD = 0.70	12	15
Total	818	M = 15.35, SD = 1.31	394	424

Note. Gray value refers to sub-sample size that is too small to allow meaningful comparisons.

Measures

Scholastic performance. Students' scholastic performance was based on test scores of midterm examinations in Math, Chinese, and English. In the Chinese education system, the midterm examination is an important test for school students. During the days before the midterm examination, all teachers of the same subject in the same grade of secondary school prepare the test items. The teachers of the same subject mark grades not knowing which student they are grading. Scores range from 0 (the worst grade) to 150 (the very best) with lower than 90 indicating insufficient performance.

NEO Five Factor Inventory (NEO-FFI). The Chinese version of the NEO-FFI was used. The questionnaire comprises 60 items, 12 items for each domain. Participants indicated the extent to which they agreed and disagreed with each item on a 5-point scale ranging from 1 *("totally disagree")* to 5 (*"totally agree"*). Reliability estimates (Omega, Ω_w, Revelle & Zinbarg, 2009) for the specified latent variables were acceptable: .83 (Neuroticism), .81 (Extraversion), .67 (Openness), .63 (Agreeableness), .82 (Conscientiousness), which is comparable to other Chinese studies using the same scale (Yao & Liang, 2010; Yangang, Boxing, & Junqian, 2010).

The Revised Two-Factor Study Process Questionnaire (R-SPQ-2F). Learning approaches were measured with a Chinese revised version of the Study Process Questionnaire (Biggs et al., 2001), including Deep-learning approach (DA) and Surface-learning approach (SA). Each of the scales comprises 10 items. We provided a 5-point Likert-type response scale ranging from 1 (*"not at all true"*) to 5 *("very true")*. Reliability estimates were: Ω_w = .74 for SA and .84 for DA.

Subject-specific self-efficacy scale. Subject-specific self-efficacy in Math, Chinese, and English (Stankov, Lee, Luo, & Hogan, 2012) was assessed with five items per domain (e.g., "I am sure I can do difficult work in my English class"). Participants indicated the extent to which they agreed and disagreed with each item on a 4-point Likert-type response scale ranging from 1 *("totally disagree")* to 4 (*"totally agree"*). Reliability estimates were: Ω_w = .89, .92, and .93 in Math, Chinese, and English, respectively.

Subject-specific self-concept scale. We used five of the PISA 2003 items to assess what Eccles and Wigfield (1995) identified as the cognitive component of subject-specific self-concept (e.g., "I am just not good at Chinese/English"). A 4-point Likert-type response scale was provided ranging from 1(*"totally disagree"*) to 4 (*"totally agree"*). Reliability estimates were: Ω_w = .88, .88, and .88 in Math, Chinese, and English, respectively.

Statistical analyses

R (R Core Team, 2012) was used to compute the descriptive statistics and correlations between all measured variables in Table 2. The proposed models were tested for each subject (see Figures 2 and 3) by means of structural equation modeling (SEM) in Mplus 7.2 (Muthén & Muthén, 1998 - 2012). Missing values were dealt with using full information maximum likelihood estimation (FIML). To judge model fit, we used the chi-square statistic, the Comparative Fit Index (CFI), the Standardized Root Mean Square Residual (SRMR), and the Root Mean Square Error of Approximation (RMSEA) with 90% confidence interval (Beauducel & Wittmann, 2005; Hu & Bentler, 1999). We deemed the fit to be acceptable with cut-offs of CFI ≥ .90, RMSEA ≤ .08, and SRMR ≤ .06 (see also Heene, Hilbert, Draxler, Ziegler, & Bühner, 2011).

Table 2. Zero-order correlations and reliability estimates for all variables tested in this study.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. N	**(.83)**															
2. E	-.37***	**(.81)**														
3. O	-.10*	.21***	**(.67)**													
4. A	.38***	-.22***	-.11*	**(.63)**												
5. C	-.43***	.25***	.26***	-.35***	**(.82)**											
6. DA	-.30***	.33***	.46***	-.27***	.53***	**(.84)**										
7. SA	.25***	-.10*	-.26***	.24***	-.31***	-.15**	**(.74)**									
8. SC_m	-.25***	.15**	.25***	-.08	.28***	.35***	-.15**	**(.88)**								
9. SE_m	-.27***	.21***	.36***	-.13**	.37***	.50***	-.22***	.64***	**(.89)**							
10. SC_c	-.08	.14**	.15**	-.09	.21***	.23***	-.09	-.22***	.07	**(.88)**						
11. SE_c	-.14**	.22***	.24***	-.17***	.29***	.34***	-.18***	-.13*	.26***	.70***	**(.92)**					
12. SC_e	-.09	.14**	.18***	-.04	.26***	.26***	-.15*	.03**	.22***	.11*	.22***	**(.88)**				
13. SE_e	-.13**	.18***	.26***	-.10**	.31***	.36***	-.19***	.02	.36***	.22***	.46***	.76***	**(.93)**			
14. Math	-.14**	.09	.22***	-.01	.18***	.28***	-.25***	.49***	.38***	-.16**	-.10*	.17***	.16**	---		
15. Chinese	-.09	.16**	.23***	-.03	.10*	.19***	-.25***	.12*	.21***	.20**	.18***	.22***	.26***	.51***	---	
16. English	-.03	.10*	.27***	.07	.08	.16**	-.24***	.17***	.24***	-.04	.02	.51***	.47***	.55***	.59***	---

Note. N varies between 722 and 807. N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness; DA = Deep-learning approach; SA = Surface-learning approach; SE_m = Math self-efficacy; SC_m = Math self-concept; SE_c = Chinese self-efficacy; SC_c = Chinese self-concept; SE_e = English self-efficacy; SC_e = English self-concept. Reliability coefficients (Omega) for specific latent variables are in brackets on the diagonal.

* $p<.05$. ** $p<.01$. *** $p<.001$.

We tested the models in three steps. First, measurement models were tested. Subject-specific self-beliefs in Math, Chinese, and English were modeled with five indicators each. All measurement models fitted the data reasonably well. The Big Five and learning approaches, were represented by three parcels each, instead of multiple indicators due to the large number of items (Little, Rhemtulla, Gibson, & Schoemann, 2013). This parceling procedure allows for the creation of item parcels that have balanced factor loadings, which helps to increase model parsimony and reduces the influence of various sources of potential measurement error associated with each individual item. Such models have zero degrees of freedom. Second, the B5NT and the DM models were tested. Our sample differs in age and gender composition, and may have different associations among the constructs across age and gender. To address this, all models were additionally tested as multiple group SEMS across different age and gender groups (Lau & Cheung, 2010). Each grade was treated as group, and the strengths of specific mediation effects between grades were compared. Similar analyses were repeated with gender as a grouping variable. Third, in order to figure out whether the mediation was full or partial, we tested each of the B5NT and the DM models twice: With and without direct effects from the Big Five to scholastic performance (Kline, 2005). The B5NT and DM models for each subject are identical in terms of degrees of freedom. Therefore, model comparison was based on the significance of the competing indirect paths. The significance of the indirect effects was determined by a bootstrap method based on 1,000 samples using 95% confidence intervals (Mallinckrodt, Abraham, Wei, & Russell, 2006; Preacher & Hayes, 2004).

Results

B5NT Models

Table 3 shows that all B5NT models fitted the data well. Moreover, chi-square difference tests showed that models including direct effects from the Big Five to scholastic performance fitted the data significantly better, indicating partial mediation. Both Openness and Conscientiousness still had significant direct effects on English grades (ßs = .18 and -.19, $p < .05$, respectively). For Conscientiousness, a suppression effect occurred (Cohen, Cohen, West, & Aiken, 1983). Extraversion still had significant direct effects on Chinese grades (ß = .14, $p < .05$). The mediation analyses (see Table 4) indicated that across all three subjects, a surface-learning approach significantly mediated the influences of Neuroticism, Openness, and Extraversion. In addition, Openness and Conscientiousness exerted their influences on scholastic performance indirectly via subject-specific self-concept but not subject-specific self-efficacy. A deep-learning approach mediated the influences of Openness and Conscientiousness on school grades but only in Math and English. Also, there were significant indirect effects of Neuroticism on Math grades mediated by Math self-concept but not Math self-efficacy.

DM Models

As can be seen, the DM models fitted the data equally well. The results, however, support only two DM based models. Conscientiousness and Openness predicted higher levels of self-efficacy in Math learning, which in turn predicted increased adoption of deep-learning approaches and ultimately better Math grades. None of the other double mediation effects reached significance. The following analyses are therefore only reported for the B5NT model.

Multiple Group SEM Analyses

Regarding age differences, the SEMs fitted the data reasonably well (see Table 5). Looking at the confidence intervals for the pairwise comparisons of indirect effects, there were mostly no significant differences with few exceptions. The indirect effect of Agreeableness on Math performance in grades 8 and 10 were significantly stronger than in grade 7. The same path with Openness as a predictor was significantly weaker in grade 10 compared to grade 8 (Tables A1, A4). For English performance the same indirect paths were significantly weaker in grade 10 compared to 8 (Tables A2, A5). For Chinese, there was a pattern showing that learning strategies were significantly weaker mediators in grade 10 compared to 8 (Tables A3, A6). The models comparing gender specific paths within grades 8 and 10 reached acceptable fits (Table 6). Only two indirect paths differed across gender (Tables A7-10). Self-concept as a mediator between Openness and Math performance was stronger for boys. The same gender difference occurred for the indirect path between Openness and English via a surface-learning approach.

Table 3. Model fits for all tested models.

School subject	Model	χ2 (*df*)	RMSEA [90% CI]	CFI	SRMR	AIC
Math	B5NT model full mediation (B5NT 1)	1093.48 (425)	.044 [.041 - .047]	.922	.047	49298.81
	B5NT model partial mediation (B5NT 2)	**1079.90 (420)**	**.044 [.041 - .047]**	**.923**	**.047**	**49294.05**
	Difference: between B5NT 1 and B5NT 2		$\Delta\chi2$ [5] = 13.58, $p < .05$			
	DM model full mediation (DM 1)	1093.48 (425)	.044 [.041 - .047]	.922	.047	49298.81
	DM model partial mediation (DM 2)	**1079.90 (420)**	**.044 [.041 - .047]**	**.923**	**.047**	**49294.05**
	Difference: between DM 1 and DM 2		$\Delta\chi2$ [5] = 13.58, $p < .05$			
Chinese	B5NT model full mediation (B5NT 1)	1121.25 (425)	.045 [.042 - .048]	.920	.048	47488.96
	B5NT model partial mediation (B5NT 2)	**1104.26 (420)**	**.045 [.041 - .048]**	**.922**	**.048**	**47481.11**
	Difference: between B5NT 1 and B5NT 2		$\Delta\chi2$ [5] = 16.99, $p < .01$			
	DM model full mediation (DM 1)	1121.25 (425)	.045 [.042 - .048]	.920	.048	47488.96
	DM model partial mediation (DM 2)	**1104.26 (420)**	**.045 [.041 - .048]**	**.922**	**.048**	**47481.11**
	Difference: between DM 1 and DM 2		$\Delta\chi2$ [5] = 16.99, $p < .01$			
English	B5NT model full mediation (B5NT 1)	1113.16 (425)	.044 [.041 - .048]	.926	.050	48436.32
	B5NT model partial mediation (B5NT 2)	**1075.11 (420)**	**.044 [.040 - .047]**	**.930**	**.048**	**48405.15**
	Difference: between B5NT 1 and B5NT 2		$\Delta\chi2$ [5] = 38.05, $p < .001$			
	DM model full mediation (DM 1)	1113.16 (425)	.044 [.041 - .048]	.926	.050	48436.32
	DM model partial mediation (DM 2)	**1075.11 (420)**	**.044 [.040 - .047]**	**.930**	**.048**	**48405.15**
	Difference: between DM 1 and DM 2		$\Delta\chi2$ [5] = 38.05, $p < .001$			

Note. RMSEA (90% CI) = root mean square error of approximation with 90% confidence internal; CFI = comparative fit index; SRMR = standardized root mean square residual; AIC = Akaike Information criterion.

Table 4. Standardized estimate and specific indirect influences of the Big Five and scholastic performance.

Models	Math grades		Chinese grades		English grades	
	Direct effects (DM/B5NT)	Indirect effects (DM/B5NT)	Direct effects (DM/B5NT)	Indirect effects (DM/B5NT)	Direct effects (DM/B5NT)	Indirect effects (DM/B5NT)
Openness	-.026/-.026		.017/.017		.180*/.180*	
→ Subject-specific self-efficacy		-.028/-.028		-.031/-.031		.001/.001
→ Subject-specific self-concept		.095**/.095**		.044*/.044*		.094**/.094**
→ Deep-learning approaches		.080**/.105**		.085$^{\#}$/.088$^{\#}$		.011/.012
→ Surface-learning approaches		.102**/.101**		.121**/.122**		.084**/.087**
→ Self-efficacy → deep approaches		.025*/—		.005/—		.001/—
Conscientiousness	-.096/-.096		-.165*/-.165*		-.191*/-.191*	
→ Subject-specific self-efficacy		-.022/-.022		-.033/-.033		.001/.001
→ Subject-specific self-concept		.125**/.125**		.062*/.062*		.179**/.179**
→ Deep-learning approaches		.109*/.129**		.105$^{\#}$/.108$^{\#}$		.014/.015
→ Surface-learning approaches		.020/.020		.024/.023		.013/.016
→ Self-efficacy → deep approaches		.020*/—		.005/—		.002/—
Extraversion	.020/.020		.136*/.136*		.058/.058	
→ Subject-specific self-efficacy		-.003/-.003		-.024/-.024		.001/.001
→ Subject-specific self-concept		.005/.005		.037/.037		.052/.052
→ Deep-learning approaches		.043/.046		.037/.040		.005/.005
→ Surface-learning approaches		-.043*/-.043*		-.049*/-.049*		-.037*/-.036*
→ Self-efficacy → deep approaches		.003/—		.004/—		.001/—
Neuroticism	.048/.048		.077/.077		.003/.003	
→ Subject-specific self-efficacy		.015/.015		-.009/-.009		.001/.001
→ Subject-specific self-concept		-.106*/-.106*		.011/.011		.012/.012
→ Deep-learning approaches		.013/.001		-.001/.001		.001/.001
→ Surface-learning approaches		-.073**/.073**		-.088*/-.087*		-.062*/-.062*
→ Self-efficacy → deep approaches		-.013/—		.001/—		.001/—
Agreeableness	.116/.116		-.011/-.011		.101/.101	
→ Subject-specific self-efficacy		.005/.015		-.004/-.004		.000/.000
→ Subject-specific self-concept		-.019/-.019		.032/.032		.109$^{\#}$/.109$^{\#}$
→ Deep-learning approaches		.083/.083		.014/.014		.002/.002
→ Surface-learning approaches		-.011/-.011		-.015/-.017		-.017/-.016
→ Self-efficacy → deep approaches		.010/—		.001/—		.001/—

Note: * $p < .05$, ** $p < .01$, $^{\#}$ $p < .10$. For better comparability, we display three decimal places for specific indirect effects obtained with the DM model (on the left side of the forward slash) and the B5NT model (on the right side of the forward slash).

Table 5. Model fits for Multiple Group SEMs Across Age.

School subject	Model	χ^2 (*df*)	RMSEA [90% CI]	CFI	SRMR	BIC
Chinese	N → multiple mediators→ grades	966.12 (524)	0.059 [0.055,0 .063]	0.931	0.058	32649.21
	E → multiple mediators→ grades	983.22(524)	0.058 [0.052,0 .063]	0.923	0.059	31383.66
	O → multiple mediators→ grades	1038.74 (524)	0.061 [0.056, 0.066]	0.918	0.067	31917.71
	A → multiple mediators→ grades	973.49 (524)	0.057 [0.051, 0.063]	0.923	0.062	32219.92
	C → multiple mediators→ grades	1052.71(524)	0.062 [0.056, 0.067]	0.922	0.059	31523.54
Math	N → multiple mediators→ grades	898.75(524)	0.052 [0.046, 0.058]	0.939	0.055	34818.99
	E → multiple mediators→ grades	941.46(524)	0.055 [0.049, 0.061]	0.930	0.059	34358.29
	O → multiple mediators→ grades	924.28(524)	0.054 [0.048, 0.059]	0.932	0.062	34108.57
	A → multiple mediators→ grades	932.62(524)	0.054 [0.049, 0.060]	0.927	0.067	34408.05
	C → multiple mediators→ grades	989.88(524)	0.058 [0.052, 0.064]	0.928	0.059	33713.04
English	N → multiple mediators→ grades	981.62(524)	0.058 [0.052, 0.063]	0.937	0.060	33783.54
	E → multiple mediators→ grades	1022.17(524)	0.060 [0.055, 0.065]	0.930	0.060	33306.00
	O → multiple mediators→ grades	1006.57(524)	0.059 [0.054, 0.065]	0.932	0.063	33054.31
	A → multiple mediators→ grades	1003.73(524)	0.062 [0.056, 0.067]	0.929	0.062	33348.33
	C → multiple mediators→ grades	1053.06(524)	0.062 [0.056, 0.067]	0.930	0.059	32643.69

Note. N = 792: Grade 7 = 105, Grade 8 = 275, Grade 10 = 412. Of note, we also attempted to run the multiple age SEMs with all the Big Five domains and all the potential mediators for each school subject, but the models do not converge. So we tested a series of multiple age SEMs separately for each of the Big Five domains and for each subject.

Table 6. Model Fits for Multiple Group SEMs Across Gender.

School subject	Model	χ^2 (*df*)	RMSEA [90% CI]	CFI	SRMR	BIC
		Grade 8				
Chinese	N → multiple mediators→ grades	560.55(340)	0.069 [0.058,0 .079]	0.914	0.080	12254.35
	E → multiple mediators→ grades	560.00(340)	0.069 [0.058, 0.079]	0.912	0.073	12136.13
	O → multiple mediators→ grades	560.55(340)	0.074 [0.064, 0.084]	0.900	0.075	12015.14
	A → multiple mediators→ grades	557.01(340)	0.068 [0.058, 0.078]	0.909	0.082	12209.68
	C → multiple mediators→ grades	544.08(340)	0.066 [0.056, 0.076]	0.922	0.074	11422.47
Math	N → multiple mediators→ grades	480.53(340)	0.055 [0.043, 0.066]	0.938	0.069	12108.78
	E → multiple mediators→ grades	475.49(340)	0.054 [0.042, 0.065]	0.938	0.068	12438.47
	O → multiple mediators→ grades	494.22(340)	0.057 [0.046, 0.068]	0.931	0.068	12316.99
	A → multiple mediators→ grades	530.70(340)	0.064 [0.053, 0.074]	0.910	0.088	12507.60
	C → multiple mediators→ grades	488.82(340)	0.056 [0.045, 0.067]	0.936	0.069	12165.94
English	N → multiple mediators→ grades	554.37(340)	0.068 [0.057, 0.078]	0.918	0.079	12415.36
	E → multiple mediators→ grades	548.23(340)	0.067 [0.056, 0.077]	0.928	0.073	12300.33
	O → multiple mediators→ grades	589.64(340)	0.073 [0.063, 0.083]	0.905	0.075	12179.41
	A → multiple mediators→ grades	548.92(340)	0.067 [0.056, 0.077]	0.914	0.083	12373.19
	C → multiple mediators→ grades	534.80(340)	0.065 [0.054, 0.075]	0.928	0.074	12018.82
		Grade 10				
Chinese	N → multiple mediators→ grades	544.76(340)	0.054 [0.046, 0.062]	0.943	0.064	15940.54
	E → multiple mediators→ grades	560.43(340)	0.056 [0.048,0 .064]	0.938	0.061	15677.57
	O → multiple mediators→ grades	607.34(340)	0.062 [0.054,0 .070]	0.924	0.076	15565.21
	A → multiple mediators→ grades	556.05(340)	0.056 [0.047, 0.064]	0.934	0.062	15647.58
	C → multiple mediators→ grades	531.64(340)	0.052 [0.044, 0.061]	0.948	0.059	15338.71
Math	N → multiple mediators→ grades	462.32(340)	0.042 [0.032, 0.051]	0.958	0.056	17074.58
	E → multiple mediators→ grades	465.44(340)	0.042 [0.032, 0.052]	0.956	0.058	16819.19
	O → multiple mediators→ grades	513.96(340)	0.050 [0.041, 0.058]	0.938	0.073	16692.78
	A → multiple mediators→ grades	475.01(340)	0.044 [0.034, 0.053]	0.948	0.063	16791.55
	C → multiple mediators→ grades	487.15(340)	0.046 [0.036, 0.055]	0.952	0.058	16489.81
English	N → multiple mediators→ grades	557.83(340)	0.056 [0.047, 0.064]	0.941	0.065	16494.82
	E → multiple mediators→ grades	568.95(340)	0.057 [0.049, 0.065]	0.937	0.062	16232.28

O → multiple mediators→ grades	614.49(340)	0.063 [0.055, 0.070]	0.923	0.077	16123.42
A → multiple mediators→ grades	568.00(340)	0.057 [0.049, 0.065]	0.932	0.062	16201.98
C → multiple mediators→ grades	534.90(340)	0.053 [0.044, 0.061]	0.948	0.060	15893.13

Note. In Grade 8, total sample N =275: Boys (N = 131) and girls (N = 144). In Grade 10, total sample N = 412: Boys (N = 198) and girls (N = 214).

Discussion

The current study was conducted in order to compare two process-based models explaining why the Big Five affect scholastic performance. Whereas the B5NT model was supported by the data, the idea of a DM model found only weak support. Our findings therefore confirmed the assumption that the Big Five exert their influences on scholastic performance via narrow traits representing self-beliefs and learning approaches.

Model Comparison

As described above, the B5NT model was strongly supported whereas the DM model was only supported for Conscientiousness and Openness and this only in Math. Denissen and Penke (2008) defined motivational reaction norms that they see as roots of the Big Five. They see differences in the tenacity of goal pursuit under distracting circumstances as the reaction norm of Conscientiousness. Differences in the activation of reward system when engaging in cognitive activity are seen as the reaction norm of Openness. These reaction norms might explain why the idea of a DM was only found for two Big Five domains. The motivational roots of the other Big Five domains are more related to social situations (Extraversion), cooperation (Agreeableness), and social exclusion (Neuroticism). Thus, it is suggested to use the B5NT instead of the DM model.

The B5NT model – Indirect Effects via Learning Approaches

Consistent with previous research (Diseth, 2003; Shokri et al., 2007; Swanberg & Martinsen, 2010), our study demonstrated that across three subjects, students who were lower in Openness and higher in Neuroticism were more likely to adopt surface-learning approaches, which in turn resulted in lower school grades. It is not surprising that students who are less open or more neurotic are less motivated to fully grasp what they learn (deep-learning approaches), thereby potentially impairing scholastic performance. As expected, students higher in Extraversion were more likely to adopt a surface-learning approach, thereby leading to lower school grades (De Raad & Schouwenburg, 1996). Here, a suppression effect for Extraversion turning the positive correlation into a negative regression weight occurred after controlling for all other variables.

In line with prior research (Shokri et al., 2007; Swanberg & Martinsen, 2010), our findings also displayed that students higher in Openness and Conscientiousness were more likely to use a deep-learning approach, thereby achieving better Math grades. The findings reflect that students higher in Openness and Conscientiousness are more motivated to truly understand what they learn, which clearly describes a deep-learning approach (Mussel, 2013). Ziegler et al. (2012) suggested that Openness influences knowledge acquisition because students higher on Openness are more motivated to actively seek and understand new information. Considering that conscientious people tend to be achievement striving (Digman, 1990), the finding that a deep-learning approach is an important mediator also seems reasonable.

Moreover, this study further extended previous findings regarding language subjects. Language is an important tool to express oneself, communicate perspectives, and experience cultures (Zhou, 2015). There might be differential effects for a native language compared with a foreign language. Our findings suggest that in general, the mechanisms found for English also worked for Chinese. Thus, there was no difference between predicting learning of the native vs. learning of a foreign language. The only exception was Openness had a direct effect on English grades while Extraversion had a direct effect on Chinese grades. The direct effect of Openness on English grades points to the importance of this trait when it comes to handling new input such as a new language including a whole new alphabet. The direct effect of Extraversion on Chinese grades specifies the importance of oral performance in language learning. However, this does not hold for English learning. Probably because English school textbooks are designed to teach grammar, vocabulary, and reading with less emphasis on listening and speaking. Such an English learning environment in China does not allow Extraversion to be a relevant predictor.

The B5NT model – Indirect Effects via Self-beliefs

Across all three subjects, subject-specific self-concept significantly mediated the influences of Openness and Conscientiousness on scholastic performance. It is not surprising that more open and more conscientious students tend to develop higher self-perceptions regarding their learning and actively solve their scholastic tasks, which helps them to achieve better school grades. Of note, our findings are consistent with a longitudinal study by Hair and Graziano (2003), where academic self-esteem mediated the effects of Openness on scholastic performance during the transition from middle to high school.

We also found that Neuroticism significantly influenced Math grades indirectly via Math self-concept. Since mathematics is associated with challenges, exam stress, and problem solving, students with higher levels of anxiety who are often preoccupied with thoughts of possible failures might lower their self-worth regarding mathematics learning, which might deteriorate their performance. Unlike in Math, there is less exam stress in language learning, so students might not be as afraid as in Math.

There were no significant indirect effects from the Big Five on scholastic performance via subject-specific self-efficacy. This is inconsistent with the study by Shams et al. (2011), indicating that self-efficacy mediated the effects of Openness and Agreeableness on Math performance. One possible explanation might be that previous research only examined the mediating role of academic self-efficacy without controlling for other relevant mediators. However, our study addressed self-beliefs and learning approaches simultaneously. Moreover, there usually is a high correlation between subject-specific self-efficacy and subject-specific self-concept (Marsh, Dowson, Pietsch, & Walker, 2004). Probably, a high proportion of the indirect effects of subject-specific self-concept were shared with those of subject-specific self-efficacy. Thus, there might not have been enough specific variance left within self-efficacy to render a significant indirect effect. This highlights the need to control for mediator overlap.

The Role of Agreeableness

Agreeableness failed to predict any of the grades. Prior studies also reported only weak but significant relationships (Poropat, 2009). Besides power issues, the reaction norm ideas by Denissen and Penke detailed above might also explain this difference to Western cultures. Another theoretical explanation potentially explaining this difference is trait activation theory (Tett & Burnett, 2003). Situational demands might distract or constrain behavior, thus yielding low test-criterion correlations. Ziegler et al. (2014) showed that the same Big Five facets predicted job-training performance only for certain jobs. In that sense, differences in behaviors associated with Agreeableness might not manifest in Chinese scholastic settings. This would mean that specific learning environments do not demand or allow cooperative behaviors. If the situation was changed, for example, by encouraging group learning and discussion in Chinese classrooms, Agreeableness might turn into a relevant predictor (Peeters, Van Tuijl, Rutte, & Reymen, 2006). Thus, the present research highlights the importance of considering situation-specific demands that might foster or hinder trait manifestation.

Age and Gender Differences in the Specific Indirect Effects

Generally, there were only a few age or gender related differences. Due to the use of cross-sectional data in this study, we cannot tell whether the differences were due to students' personality maturation or the materials being taught. However, when zooming into the specific indirect effects, it seems that learning approaches are more important for middle school students, while self-beliefs are more vital for high school students.

Limitations and Suggestions for Future Research

This study relies on self-report data. Previous studies showed that other-rated personality measures also have strong correlations with academic performance (Ziegler, Danay, Schölmerich, & Bühner, 2010; Poropat, 2014). Thus, the current findings might underestimate the potential strength of the relationships which might be revealed when incorporating different points of views. Second, the Big Five personality traits were measured on the domain level, which may lead to lower predictor-criterion correlations. Previous research has suggested that faceted measures are more powerful predictors than the broader domains (e.g., Ziegler, Danay, Schölmerich, & Bühner, 2010). Future research should include facet measures of the Big Five to further elucidate the specific aspects of each domain driving motivation and learning strategies and thereby influencing scholastic performance. Third, our samples differed regarding age and gender. A series of multiple group analyses indicated that several indirect influences of personality traits on scholastic performance did differ significantly across both age and gender. Due to the use of cross-sectional data in the current study, it remains unclear whether the differences between several mediation effects are due to students' personality maturation or the materials being taught. However, the consistency between the present findings and prior findings from longitudinal studies suggests that the underlying processes are the same. Future research should examine the integrated process model in a longitudinal cross-lagged study. In sum, the limitations also point out several avenues for future research.

Conclusions and Implications

In conclusion, this study provides initial evidence for self-beliefs and learning approaches as mechanism explaining how personality traits affect scholastic performance. One of the current study's strengths is its use of a multivariate approach allowing the isolation of specific mediation effects. Also, our study emphasizes the importance of considering specific subjects when predicting scholastic performance. In terms of the present findings, Math learning might be viewed as being different from language learning.

Above and beyond the B5NT model does not only provide a framework for further empirical research, it also suggests that narrow traits could be targeted in academic interventions. Specifically, self-beliefs and learning approaches are more malleable than personality traits and still have direct influences on outcomes. For example, providing reinforcement for students who adopt deep-learning approaches might translate into higher levels of scholastic performance than giving vague instructions to become more conscientious.

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Supplementary Materials

Table A1. *Estimate and Bias-Corrected Confidence Intervals for Differences between Specific Indirect Effects (DI) in Mathematics*

Mathematics	Between Grade 7 and 8				Between Grade 7 and 10				Between Grade 8 and 10			
			95%CI				95%CI				95%CI	
New/additional Parameters	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper
Agreeableness												
DI-deep approach	.051	.816	-.201	.757	-.044	.684	-.327	.128	-.095	.686	-.790	.225
DI-surface approach	-1.104	.464	-5.200	1.011	-1.464	.308	-5.495	.293	-.361	.409	-1.309	.412
DI-self-concept	**-2.369**	**.104**	**-5.456**	**-.036**	**-1.830**	**.165**	**-5.673**	**-.107**	.539	.523	-1.040	2.314
DI-self-efficacy	-.137	.892	-2.504	1.391	.178	.857	-2.146	1.825	.315	.396	-.403	1.205
Openness												
DI-deep approach	44.01	.622	-19.53	356.46	37.52	.672	-25.99	366.66	-6.49	.390	-21.69	8.44
DI-surface approach	9.10	.718	-7.85	102.87	11.59	.646	-3.61	115.16	2.49	.469	-4.81	8.78
DI-self-concept	-8.53	.526	-30.08	21.36	1.47	.909	-18.86	33.73	**10.01**	**.052**	**2.01**	**22.69**
DI-self-efficacy	1.106	.970	-34.13	93.56	4.06	.887	-27.04	108.56	2.96	.644	-10.26	14.81
Neuroticism												
DI-deep approach	-7.05	.505	-26.19	4.23	-9.15	.381	-26.98	.80	-2.09	.398	-7.38	2.76
DI-surface approach	-2.32	.808	-21.15	7.24	-6.19	.506	-25.42	1.63	-3.87	.107	-9.46	0.28
DI-self-concept	2.49	.720	-11.51	14.28	-0.12	.986	-13.29	9.11	-2.61	.485	-11.36	3.89
DI-self-efficacy	0.48	.968	-19.20	16.78	-1.12	.923	-20.89	13.46	-1.59	.602	-7.26	5.02
Extraversion												
DI-deep approach	9.33	.644	-11.84	59.33	10.78	.589	-11.38	59.10	1.45	.725	-5.855	10.701
DI-surface approach	-1.33	.855	-14.17	15.48	1.92	.778	-9.91	18.16	3.25	.237	-.720	10.060
DI-self-concept	-2.01	.808	-18.32	12.41	-.669	.928	-11.81	12.67	1.34	.747	-6.170	10.590
DI-self-efficacy	-3.26	.818	-30.05	21.95	-2.12	.879	-26.79	23.65	1.14	.716	-5.095	7.785
Conscientiousness												
DI-deep approach	13.121	.242	-5.881	33.990	10.942	.346	-7.015	33.837	-2.179	.747	-16.117	11.194
DI-surface approach	1.255	.835	-8.179	15.585	3.421	.573	-5.748	17.780	2.166	.489	-4.320	8.590
DI-self-concept	-3.909	.573	-16.868	10.230	-1.678	.791	-11.303	13.190	2.231	.617	-5.597	12.237
DI-self-efficacy	.146	.989	-18.453	19.777	4.236	.679	-13.685	24.866	4.090	.409	-5.719	13.578

Table A2. Estimate and Bias-Corrected Confidence Intervals for Differences between Specific Indirect Effects (DI) in English

English	Between Grade 7 and 8				Between Grade 7 and 10				Between Grade 8 and 10			
			95%CI				95%CI				95%CI	
New/additional Parameter	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper
Agreeableness												
DI-deep approach	-.033	.838	-.426	.285	-.019	.816	-.171	.150	.014	.932	-.292	.424
DI-surface approach	-.615	.509	-3.198	.614	-.859	.326	-3.167	.278	-.243	.510	-1.141	.405
DI-self-concept	-2.288	.204	-5.809	.338	.283	.842	-2.102	2.698	**2.571**	**.029**	**.561**	**5.351**
DI-self-efficacy	-.106	.929	-2.781	1.386	-.226	.846	-3.304	1.003	-.119	.730	-1.009	.488
Openness												
DI-deep approach	-9.313	.890	-378.411	37.874	-9.553	.887	-395.269	37.453	-.241	.972	-13.132	13.259
DI-surface approach	-.396	.980	-44.787	24.356	-.030	.998	-38.489	26.126	.367	.897	-4.659	6.191
DI-self-concept	-11.468	.469	-31.678	37.954	-.062	.997	-15.539	60.084	**11.407**	**.052**	**1.635**	**25.753**
DI-self-efficacy	.772	.971	-42.589	37.501	3.297	.873	-40.622	34.799	2.525	.639	-7.894	13.575
Neuroticism												
DI-deep approach	-5.662	.502	-20.806	3.349	**-7.539**	**.360**	**-23.250**	**-.129**	-1.877	.438	-6.958	2.449
DI-surface approach	-1.893	.784	-17.433	5.754	-3.147	.637	-17.489	3.424	-1.254	.559	-5.709	2.547
DI-self-concept	2.117	.829	-16.772	20.468	-.455	.960	-22.651	14.855	-2.572	.545	-12.144	4.498
DI-self-efficacy	-3.256	.743	-23.991	12.285	-3.809	.694	-25.569	9.433	-.552	.789	-4.415	3.991
Extraversion												
DI-deep approach	7.133	.622	-9.050	38.388	7.975	.577	-8.161	41.381	.842	.803	-5.162	7.804
DI-surface approach	-1.202	.807	-9.912	9.381	.601	.895	-6.601	11.080	1.803	.392	-1.461	6.885
DI-self-concept	-8.734	.391	-27.490	11.022	-1.206	.895	-13.370	21.030	7.529	.149	-1.629	18.641
DI-self-efficacy	4.472	.772	-20.790	36.676	4.698	.750	-19.407	32.870	.226	.954	-8.478	7.374
Conscientiousness												
DI-deep approach	7.007	.438	-10.057	24.247	7.626	.373	-7.226	25.641	.619	.912	-9.818	11.528
DI-surface approach	.252	.957	-7.443	10.121	-.537	.906	-7.673	9.077	-.789	.769	-6.994	4.221
DI-self-concept	-14.931	.129	-34.716	5.794	-5.913	.453	-20.531	12.049	9.018	.159	-1.768	23.047
DI-self-efficacy	4.726	.640	-12.846	26.698	6.428	.479	-8.178	28.701	1.702	.725	-8.405	10.294

Table A3. Estimate and Bias-Corrected Confidence Intervals for Differences between Specific Indirect Effects (DI) in Chinese

Chinese	Between Grade 7 and 8				Between Grade 7 and 10				Between Grade 8 and 10			
			95%CI				95%CI				95%CI	
New/additional Parameter	Estimate	*p*-value	Lower	Upper	Estimate	*p*-value	Lower	Upper	Estimate	*p*-value	Lower	Upper
Agreeableness												
DI-deep approach	**-2.064**	**.809**	**-10.601**	**-0.020**	-.310	.971	-8.323	.889	**2.374**	**.078**	**.040**	**4.738**
DI-surface approach	1.067	.777	-3.773	13.291	3.529	.312	-.303	15.032	**2.462**	**.088**	**.036**	**5.860**
DI-self-concept	1.257	.676	-2.099	10.499	1.088	.715	-1.803	10.905	-.168	.834	-1.474	1.969
DI-self-efficacy	2.151	.527	-4.504	10.155	1.817	.590	-3.011	9.585	-.334	.754	-2.843	1.279
Openness												
DI-deep approach	-30.493	.653	-366.437	20.402	-27.106	.688	-362.508	22.391	3.387	.542	-7.043	15.123
DI-surface approach	.788	.967	-20.884	51.762	4.908	.796	-15.039	55.755	**4.120**	**.101**	**.157**	**10.536**
DI-self-concept	9.925	.628	-3.894	84.206	8.660	.672	-4.152	88.459	-1.265	.573	-4.948	4.110
DI-self-efficacy	6.625	.774	-44.193	35.531	6.387	.782	-45.667	34.362	-.238	.932	-7.504	4.419
Neuroticism												
DI-deep approach	1.433	.892	-21.526	16.519	-2.991	.771	-25.812	11.268	**-4.424**	**.041**	**-9.677**	**-1.120**
DI-surface approach	-3.024	.703	-26.448	5.756	-7.040	.363	-29.612	.328	**-4.016**	**.042**	**-8.589**	**-1.099**
DI-self-concept	0.847	.850	-7.260	8.257	.659	.877	-9.670	6.753	-.188	.907	-5.086	2.064
DI-self-efficacy	-3.299	.584	-16.089	5.886	-2.487	.672	-15.250	5.001	**.812**	**.610**	**-1.128**	**5.582**
Extraversion												
DI-deep approach	-9.244	.651	-59.779	7.966	-4.524	.820	-57.180	10.619	**4.720**	**.117**	**.049**	**11.888**
DI-surface approach	-1.234	.857	-13.082	14.335	1.802	.786	-7.808	17.074	**3.036**	**.158**	**-.079**	**8.487**
DI-self-concept	1.972	.856	-8.511	33.800	4.910	.643	-3.402	34.963	2.938	.304	-1.340	9.730
DI-self-efficacy	6.507	.627	-18.244	25.476	3.404	.794	-17.512	22.481	-3.103	.366	-11.541	2.003
Conscientiousness												
DI-deep approach	-3.847	.809	-27.589	21.911	1.263	.936	-19.608	28.323	5.109	.220	-1.609	15.112
DI-surface approach	0.827	.912	-7.058	16.981	4.393	.545	-2.460	21.205	**3.567**	**.074**	**0.378**	**8.469**
DI-self-concept	2.293	.736	-4.007	27.526	1.972	.770	-3.277	27.595	-.321	.870	-3.255	4.739
DI-self-efficacy	4.099	.567	-7.758	14.499	2.651	.697	-8.044	11.956	-1.448	.617	-8.809	2.912

Table A4. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects for Mathematics in Grade 7, 8, and 10

Mathematics	Grade 7			Grade 8			Grade 10		
		95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness									
→ Deep approaches	-.001	-.003	.001	-.002	-.015	.010	.001	-.007	.009
→ Surface approaches	-.040	-.114	.035	-.011	-.036	.014	-.001	-.008	.007
→ Self-concept	-.025	-.091	.040	.043	.001	.085	.037	.002	.072
→ Self-efficacy	-.004	-.055	.047	.000	-.016	.016	-.013	-.034	.007
Openness									
→ Deep approaches	.427	-1.118	1.971	.013	-.141	.167	.125	-.025	.275
→ Surface approaches	.141	-.280	.561	.076	.010	.143	.054	-.016	.124
→ Self-concept	.062	-.146	.270	.201	.085	.318	.085	.012	.158
→ Self-efficacy	.000	-.508	.508	-.014	-.162	.133	-.068	-.154	.018
Neuroticism									
→ Deep approaches	-.171	-.488	.146	-.054	-.124	.015	-.032	-.082	.017
→ Surface approaches	-.125	-.418	.258	-.085	-.150	-.020	-.036	-.089	.017
→ Self-concept	-.108	-.294	.077	-.144	-.244	-.044	-.156	-.244	-.069
→ Self-efficacy	.021	-.322	.364	.013	-.068	.093	.057	-.018	.133
Extraversion									
→ Deep approaches	.163	-.264	.590	.051	-.041	.143	.049	-.013	.111
→ Surface approaches	.029	-.127	.186	-.047	-.018	.112	.009	-.013	.031
→ Self-concept	.040	-.118	.198	.067	-.024	.159	.075	-.001	.151
→ Self-efficacy	-.044	-.368	.279	-.005	-.077	.067	-.029	-.071	.013
Conscientiousness									
→ Deep approaches	.316	-.047	.679	.073	-.059	.205	.149	-.062	.359
→ Surface approaches	.113	-.083	.308	.079	.012	.146	.063	-.029	.155
→ Self-concept	.129	-.074	.332	.173	.058	.287	.193	.097	.290
→ Self-efficacy	-.002	-.293	.345	-.004	-.132	.124	-.094	-.202	.014

Table A5. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects for English in Grade 7, 8, and 10

English	Grade 7			Grade 8			Grade 10		
		95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness									
→ Deep approaches	-.001	-.004	.002	.000	-.009	.009	-.001	-.007	.006
→ Surface approaches	-.032	-.091	.027	-.008	-.026	.011	-.002	-.016	.013
→ Self-concept	.002	-.097	.101	.066	.006	.127	-.011	-.050	.028
→ Self-efficacy	-.005	-.089	.079	-.001	-.017	.015	.004	-.013	.022
Openness									
→ Deep approaches	-.174	-1.724	1.375	-.056	-.207	.096	-.083	-.203	.037
→ Surface approaches	.042	-.313	.396	.047	-.013	.106	.066	.009	.123
→ Self-concept	.078	-.282	.438	.223	.103	.343	.124	.016	.231
→ Self-efficacy	.000	-.507	.507	-.010	-.128	.109	-.066	-.158	.026
Neuroticism									
→ Deep approaches	-.147	-.468	.174	-.017	-.082	.048	.020	-.026	.066
→ Surface approaches	-.126	-.396	.143	-.058	-.111	-.006	-.077	-.136	-.017
→ Self-concept	-.060	-.437	.318	-.072	-.185	.041	-.065	-.162	.032
→ Self-efficacy	-.058	-.472	.356	.009	-.043	.060	.032	-.021	.085
Extraversion									
→ Deep approaches	.115	-.318	.548	-.001	-.076	.074	-.022	-.073	.029
→ Surface approaches	.023	-.119	.165	.032	-.015	.079	.018	-.012	.049
→ Self-concept	.035	-.246	.316	.133	.018	.247	.077	-.023	.177
→ Self-efficacy	.057	-.412	.527	-.012	-.103	.079	-.027	-.077	.023
Conscientiousness									
→ Deep approaches	.233	-.126	.592	.041	-.084	.166	.057	-.115	.228
→ Surface approaches	.100	-.087	.287	.058	.001	.116	.123	.034	.212
→ Self-concept	.052	-.297	.401	.252	.093	.412	.209	.093	.326
→ Self-efficacy	.072	-.338	.482	-.025	-.147	.097	-.088	-.199	.023

Table A6. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects for Chinese in Grade 7, 8, and 10

Chinese	Grade 7			Grade 8			Grade 10		
		95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness									
→ Deep approaches	.018	-.502	.538	.115	.009	.220	.032	-.035	.099
→ Surface approaches	.118	-.086	.322	.121	.005	.237	.039	-.049	.127
→ Self-concept	.052	-.127	.230	.019	-.037	.075	.070	-.031	.171
→ Self-efficacy	.036	-.166	.237	-.043	-.124	.038	-.075	-.169	.019
Openness									
→ Deep approaches	-.277	-1.645	1.091	.097	-.098	.291	.072	-.055	.198
→ Surface approaches	.062	-.284	.408	.097	.007	.186	.037	-.032	.106
→ Self-concept	.132	-.265	.530	.045	-.023	.113	.166	.051	.282
→ Self-efficacy	.044	-.415	.503	-.050	-.141	.041	-.108	-.229	.013
Neuroticism									
→ Deep approaches	-.062	-.428	.304	-.108	-.194	-.023	-.023	-.070	.024
→ Surface approaches	-.138	-.413	.137	-.100	-.180	-.021	-.027	-.090	.035
→ Self-concept	-.006	-.151	.140	-.026	-.089	.036	-.064	-.144	.016
→ Self-efficacy	-.033	-.241	.175	.034	-.030	.099	.046	-.017	.108
Extraversion									
→ Deep approaches	-.057	-.555	.441	.097	-.003	.196	.025	-.027	.077
→ Surface approaches	.027	-.146	.199	.059	-.015	.134	.007	-.014	.027
→ Self-concept	.086	-.186	.358	.078	-.018	.175	.066	-.013	.145
→ Self-efficacy	.031	-.308	.370	-.081	-.199	.038	-.064	-.141	.012
Conscientiousness									
→ Deep approaches	.069	-.578	.717	.164	.010	.318	.130	-.051	.311
→ Surface approaches	.106	-.189	.400	.099	.022	.176	.050	-.040	.141
→ Self-concept	.088	-.182	.358	.046	-.023	.116	.142	.025	.258
→ Self-efficacy	.020	-.255	.295	-.070	-.184	.043	-.100	-.212	.011

Table A7. *Estimate and Bias-Corrected Confidence Intervals for Gender Differences between Specific Indirect Effects (DI) in Grade 8*

	Gender difference											
	Mathematics				English				Chinese			
			95%CI				95%CI				95%CI	
New/additional Parameters	Estimate	*p*-value	Lower	Upper	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper
Agreeableness												
DI-deep approach	-1.510	.972	-125.56	22.91	-12.061	.832	-194.49	8.56	-18.271	.826	-351.09	6.91
DI-surface approach	6.681	.834	-30.68	55.06	5.362	.797	-25.32	39.69	1.166	.963	-46.22	20.32
DI-self-concept	17.239	.513	-19.74	77.03	11.903	.701	-40.87	77.04	4.379	.809	-22.73	48.08
DI-self-efficacy	-3.470	.902	-62.33	38.09	2.935	.920	-26.81	72.71	1.301	.967	-24.56	93.75
Openness												
DI-deep approach	-3.454	.822	-33.71	27.59	9.861	.766	-48.26	78.37	18.143	.513	-33.24	75.99
DI-surface approach	-2.803	.672	-15.72	9.77	-3.231	.679	-17.65	11.10	-.658	.903	-9.84	12.51
DI-self-concept	-4.736	.729	-34.64	18.56	-3.466	.897	-41.57	63.26	-1.730	.931	-29.66	58.26
DI-self-efficacy	12.912	.445	-16.25	48.40	-5.971	.833	-73.45	41.72	-2.693	.903	-71.07	30.83
Neuroticism												
DI-deep approach	-1.241	.842	-15.49	9.31	-8.886	.454	-41.14	3.58	-10.588	.292	-43.74	.120
DI-surface approach	6.900	.149	-2.14	16.46	4.567	.315	-3.94	14.04	2.478	.469	-4.359	9.19
DI-self-concept	.297	.970	-18.07	12.22	3.690	.744	-19.37	25.81	1.183	.834	-8.75	11.64
DI-self-efficacy	-2.267	.686	-14.27	9.03	3.239	.753	-4.89	35.83	1.402	.868	-4.77	29.55
Extraversion												
DI-deep approach	-1.750	.882	-21.38	20.94	9.426	.612	-16.53	45.36	15.479	.356	-5.83	57.07
DI-surface approach	-4.619	.514	-22.48	6.22	-3.396	.553	-18.10	5.34	-1.839	.684	-12.52	5.73
DI-self-concept	4.262	.678	-14.29	26.96	10.039	.616	-17.94	50.49	2.693	.851	-10.66	39.04
DI-self-efficacy	6.275	.543	-12.63	29.88	-11.723	.689	-73.27	22.21	-4.243	.868	-66.23	21.27
Conscientiousness												
DI-deep approach	1.316	.909	-19.38	23.21	8.444	.671	-20.79	48.58	17.793	.302	-9.70	54.68
DI-surface approach	-1.331	.790	-10.66	10.11	-1.701	.706	-9.85	7.94	-.241	.948	-6.19	9.77
DI-self-concept	-7.322	.526	-28.80	16.31	-23.47	.182	-56.65	6.09	-8.175	.420	-24.98	12.05
DI-self-efficacy	9.507	.456	-14.72	35.69	-4.873	.794	-44.42	17.89	-3.056	.837	-31.60	14.82

Table A8. Estimate and Bias-Corrected Confidence Intervals for Gender Differences between Specific Indirect Effects (DI) in Grade 10

	Gender difference											
	Mathematics				English				Chinese			
			95%CI				95%CI				95%CI	
New/additional Parameters	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper	Estimate	*p-value*	Lower	Upper
Agreeableness												
DI-deep approach	15.651	.383	-2.05	70.73	.380	.963	-13.40	18.08	3.231	.512	-2.29	17.45
DI-surface approach	10.547	.660	-12.65	75.96	-2.108	.890	-26.08	29.64	-2.082	.792	-15.55	13.12
DI-self-concept	-2.080	.853	-29.70	18.45	-.417	.975	-24.91	26.72	-2.231	.554	-12.31	1.44
DI-self-efficacy	-7.198	.409	-30.31	5.61	11.997	.420	-9.42	47.73	3.885	.601	-4.74	20.26
Openness												
DI-deep approach	2.487	.930	18.48	72.85	2.994	.787	-21.17	20.45	-1.257	.749	-8.30	6.32
DI-surface approach	8.276	.561	-3.14	49.04	**10.21**	**.198**	**.95**	**29.36**	2.058	.348	-1.46	7.02
DI-self-concept	**10.755**	**.218**	**1.28**	**35.62**	6.166	.397	-4.74	23.03	3.005	.378	-.337	10.30
DI-self-efficacy	2.065	.840	-28.61	14.90	-8.463	.320	-28.56	1.38	-3.119	.442	-11.57	.97
Neuroticism												
DI-deep approach	3.644	.171	-1.36	9.31	.374	.845	-3.01	4.19	.785	.403	-1.03	2.57
DI-surface approach	.539	.855	-5.84	5.86	-2.906	.362	-10.99	1.74	-1.322	.305	-4.65	.67
DI-self-concept	-.526	.885	-8.77	6.05	-1.692	.721	-12.23	5.94	-.934	.451	-5.06	.35
DI-self-efficacy	-3.810	.266	-10.72	3.04	3.372	.477	-1.19	16.17	1.166	.495	-.56	5.30
Extraversion												
DI-deep approach	-6.363	.134	-16.22	1.15	.550	.863	-5.34	5.82	-1.110	.488	-4.29	1.76
DI-surface approach	-.142	.909	-2.83	2.37	.959	.674	-2.41	6.06	.288	.693	-.62	2.50
DI-self-concept	3.155	.491	-4.46	13.43	-6.160	.321	-18.33	4.51	.441	.770	-2.22	2.97
DI-self-efficacy	1.890	.548	-4.07	9.06	2.782	.540	-3.67	13.44	-.547	.729	-3.31	2.62
Conscientiousness												
DI-deep approach	-9.581	.409	-33.88	10.77	3.214	.752	-11.02	19.42	-1.257	.749	-8.304	6.32
DI-surface approach	-.624	.901	-10.94	7.94	5.884	.315	-1.128	21.23	2.058	.348	-1.461	7.02
DI-self-concept	2.980	.558	-5.70	15.41	10.087	.259	-.489	25.69	3.005	.378	-.337	10.30
DI-self-efficacy	5.072	.411	-7.41	16.89	-9.378	.349	-29.30	.253	-3.119	.442	-11.57	.97

Table A9. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects in Mathematics for Boys and Girls

Mathematics	Grade 8 (boys)			Grade 8 (girls)			Grade 10 (boys)			Grade 10 (girls)		
		95%CI			95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness												
→ Deep approaches	-.066	-.519	.387	-.060	-.203	.083	.005	-.122	.133	-.142	-.393	.108
→ Surface approaches	-.055	-.442	.332	-.127	-.371	.118	-.047	-.154	.060	-.143	-.503	.216
→ Self-concept	.038	-.247	.324	-.123	-.364	.118	-.056	-.191	.079	-.032	-.157	.092
→ Self-efficacy	.003	-.194	.200	.037	-.187	.262	.006	-.095	.107	.073$^{\#}$	-.027	.173
Openness												
→ Deep approaches	-.008	-.338	.322	.033	-.177	.243	.170	-.611	.951	.180$^{\#}$	-.038	.397
→ Surface approaches	.057	-.046	.160	.082$^{\#}$	-.030	.195	.162	-.240	.563	.041	-.046	.129
→ Self-concept	.181$^{\#}$	-.086	.449	.214***	.055	.373	**.189$^{\#}$**	**-.050**	**.427**	**.024**	**-.069**	**.118**
→ Self-efficacy	.072	-.245	.389	-.088	-.322	.147	-.055	-.350	.239	-.121*	-.251	.008
Neuroticism												
→ Deep approaches	-.053	-.216	.109	-.048	-.139	.042	.022	-.078	.122	-.068*	-.135	.000
→ Surface approaches	-.033	-.114	.048	-.176**	-.315	-.037	-.034	-.131	.063	-.053	-.146	.039
→ Self-concept	-.097	-.281	.086	-.137*	-.272	-.001	-.127*	-.251	-.003	-.134**	-.246	-.022
→ Self-efficacy	-.007	-.114	.100	.034	-.115	.182	.008	-.102	.118	.106$^{\#}$	-.009	.222
Extraversion												
→ Deep approaches	.033	-.207	.273	.049	-.042	.139	-.027	-.152	.098	.104**	.012	.196
→ Surface approaches	.024	-.049	.096	.071	-.054	.196	.006	-.027	.040	.010	-.022	.043
→ Self-concept	.101	-.081	.284	.047	-.070	.164	.121$^{\#}$	-.011	.254	.073$^{\#}$	-.028	.174
→ Self-efficacy	.042	-.148	.232	-.029	-.140	.082	-.005	-.099	.089	-.046	-.113	.020
Conscientiousness												
→ Deep approaches	.079	-.169	.328	.061	-.135	.257	.031	-.331	.394	.238$^{\#}$	-.092	.568
→ Surface approaches	.050	-.040	.139	.069	-.021	.159	.060	-.088	.209	.072	-.083	.226
→ Self-concept	.147$^{\#}$	-.060	.354	.254**	.054	.454	.228**	.044	.412	.155**	.029	.281
→ Self-efficacy	.059	-.175	.294	-.077	-.326	.172	-.031	-.253	.191	-.140*	-.286	.006

Table A10. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects in English for Boys and Girls

English	Grade 8 (boys)			Grade 8 (girls)			Grade 10 (boys)			Grade 10 (girls)		
		95%CI			95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness												
→ Deep approaches	-.083	-.653	.488	.020	-.082	.122	-.002	-.101	.096	-.007	-.124	.110
→ Surface approaches	-.036	-.197	.126	-.090	-.261	.080	-.133*	-.271	.005	-.120	-.384	.144
→ Self-concept	.033	-.293	.358	-.074	-.286	.138	-.091	-.299	.117	-.093	-.254	.065
→ Self-efficacy	.009	-.335	.353	-.017	-.109	.076	.142	-.111	.395	.015	.132	.163
Openness												
→ Deep approaches	.027	-.737	.791	-.083	-.271	.104	-.003	-.349	.343	-.092	-.289	.105
→ Surface approaches	.031	-.098	.161	.063	-.039	.165	**.198**	**-.071**	**.468**	**.020**	**-.040**	**.081**
→ Self-concept	.227	-.352	.806	.236*	.070	.402	.175	-.074	.424	.101	-.030	.231
→ Self-efficacy	-.049	-.700	.602	.022	-.142	.186	-.179	-.475	.116	-.041	-.135	.054
Neuroticism												
→ Deep approaches	-.100	-.405	.204	.020	-.047	.087	.016	-.068	.100	.009	-.049	.067
→ Surface approaches	-.023	-.090	.043	-.112#	-.233	.009	-.120#	-.257	.016	-.063	-.152	.025
→ Self-concept	-.009	-.253	.235	-.077	-.252	.098	-.111	-.319	.098	-.092	-.224	.040
→ Self-efficacy	.039	-.219	.296	-.005	-.065	.055	.102	-.119	.323	.023	-.050	.096
Extraversion												
→ Deep approaches	.079	-.310	.468	-.025	-.092	.042	.004	-.111	.120	-.010	-.076	.056
→ Surface approaches	.015	-.047	.077	.049	-.047	.145	.026	-.063	.116	.008	-.016	.032
→ Self-concept	.203	-.184	.590	.081	-.067	.229	-.034	-.256	.188	.131#	-.006	.267
→ Self-efficacy	-.123	-.728	.482	.009	-.058	.075	.035	-.128	.198	-.032	-.123	.058
Conscientiousness												
→ Deep approaches	.130	-.381	.642	.013	-.132	.158	.143	-.314	.600	.067	-.186	.319
→ Surface approaches	.032	-.055	.118	.056	-.021	.133	.223#	-.048	.495	.079	-.040	.198
→ Self-concept	.083	-.270	.436	.414**	.176	.652	.375#	-.079	.830	.128*	.003	.252
→ Self-efficacy	-.063	-.526	.399	.005	-.171	.181	-.272	-.782	.237	-.033	-.156	.091

Table A11. Standardized Estimate and Bias-Corrected Confidence Intervals for Specific Indirect Effects in Chinese for Boys and Girls

Chinese	Grade 8 (boys)			Grade 8 (girls)			Grade 10 (boys)			Grade 10 (girls)		
		95%CI			95%CI			95%CI			95%CI	
Indirect Effects	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Agreeableness												
→ Deep approaches	-.170	-1.079	.740	.042	-.075	.158	-.007	-.112	.098	-.086	-.258	.087
→ Surface approaches	-.049	-.313	.214	-.098	-.275	.079	-.087	-.238	.063	-.028	-.335	.279
→ Self-concept	.010	-.251	.271	-.059	-.213	.095	-.026	-.152	.101	.032	-.084	.147
→ Self-efficacy	.010	-.429	.450	-.006	-.108	.096	.047	-.180	.274	-.053	-.280	.174
Openness												
→ Deep approaches	.205	-.674	1.084	-.127	-.338	.084	.074	-.314	.462	.146$^{\#}$	-.034	.325
→ Surface approaches	.056	-.091	.203	.081	-.040	.201	.172	-.085	.429	.010	-.057	.078
→ Self-concept	.098	-.519	.714	.153$^{\#}$	-.016	.323	.052	-.102	.205	-.029	-.109	.050
→ Self-efficacy	-.036	-.730	.657	.012	-.166	.189	-.072	-.342	.199	.047	-.059	.153
Neuroticism												
→ Deep approaches	-.175	-.535	.186	.026	-.053	.105	.002	-.091	.095	-.052	-.116	.013
→ Surface approaches	-.029	-.108	.049	-.139$^{\#}$	-.291	.014	-.086	-.214	.042	-.006	-.096	.085
→ Self-concept	-.005	-.179	.169	-.049	.180	.082	-.033	-.156	.090	.028	-.054	.109
→ Self-efficacy	.024	-.271	.318	-.002	-.070	.066	.042	-.140	.223	-.034	-.120	.052
Extraversion												
→ Deep approaches	.206	-.249	.662	-.039	-.127	.050	.003	-.134	.140	.068	-.014	.150
→ Surface approaches	.023	-.056	.101	.064	-.062	.190	.017	-.051	.085	.002	-.021	.025
→ Self-concept	.083	-.313	.479	.053	-.057	.163	-.010	-.126	.105	-.037	-.128	.054
→ Self-efficacy	-.061	-.786	.663	.004	-.065	.074	.014	-.100	.128	.047	-.057	.152
Conscientiousness												
→ Deep approaches	.319	-.291	.930	-.025	-.185	.135	.123	-.274	.519	.188	-.072	.449
→ Surface approaches	.046	-.057	.150	.072	-.028	.171	.153	-.069	.376	.021	-.102	.144
→ Self-concept	.040	-.272	.352	.274**	.038	.509	.143	-.259	.545	-.044	-.148	.059
→ Self-efficacy	-.055	-.574	.463	.003	-.196	.203	-.125	-.597	.348	.068	-.072	.208

A Three-Wave Longitudinal Study: A Process Model from Personality to Scholastic Performance

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Abstract: Our study tested the Big Five-Narrow Traits (B5NT) model explaining the relation between personality traits and scholastic performance. This longitudinal study involved three measurement points in a sample of 836 Chinese secondary school students (M_{age} = 15.35; 406 girls) over the course of one academic year. Longitudinal mediation analyses were applied. Results support the idea of the B5NT model and demonstrate that for the three subjects Math, English and Chinese, Conscientiousness and Neuroticism influence schools grades through surface learning approaches. For Math, all of the FFM traits except for Extraversion influence Math grades via Math self-efficacy. Openness and Neuroticism also influence Math grades via Math self-concept. For Chinese and English, Openness, Conscientiousness, and Agreeableness exert their effects on school grades via deep learning approaches. For English, Conscientiousness affects English grades via English self-concept, while Neuroticism influences English grades via deep learning approaches. In addition, two reverse longitudinal mediation effects suggest that prior performance could also predict subsequent levels of self-beliefs and learning approaches, and ultimately might affect personality development. Thus, an extension to the B5NT model is suggested. Is also discussed how narrow traits like self-beliefs and learning approaches might serve as effective targets for future academic interventions.

Keywords: Big Five-Narrow Traits model, self-beliefs, learning approaches, scholastic performance, sociogenomic model of personality

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The determinants of scholastic performance have captured the attention of many scholars over the last decades (Robbins et al., 2004). Intelligence is well known to be a strong predictor of scholastic performance (Deary, Strand, Smith, & Fernandes, 2007; Gottfredson, 2002; Kuncel, Hezlett, & Ones, 2004). Above and beyond intelligence, personality as defined in the Five-Factor Model has been found to contribute to performance across varying educational settings (De Raad & Schouwenburg, 1996; Poropat, 2009; Richardson, Abraham, & Bond, 2012). Surprisingly, very few studies have addressed the role of intervening processes that might explain why this is the case. As conceived with the analysis level model of personality perspective (Graziano, Jensen-Campbell, & Finch, 1997; McAdams, 1995; McAdams & Pals, 2006) and surface-core traits theory (Marsh & Craven, 2006), we proposed and tested a Big Five-Narrow Traits (B5NT) model with learning approaches and self-belief systems (e.g., academic self-efficacy and academic self-concept) as intervening variables between personality and scholastic performance (Zhang & Ziegler, under review). So far, the B5NT model has only been tested cross-sectionally, which might limit the conclusions that can be drawn. Consequently, the present study attempted to test the B5NT model among 836 Chinese secondary school students within a three-wave longitudinal panel design.

Personality and Scholastic performance

It has been shown that after controlling for the influences of fluid intelligence, the Big Five domains contribute to scholastic performance (e.g., Zhang & Ziegler, 2015). Especially Conscientiousness and Openness have been indicated as consistent predictors in meta-analyses (Poropat, 2009; Richardson et al., 2012). Moreover, several previous studies also emphasized the importance of considering specific subjects when predicting scholastic performance (Furnham & Monsen, 2009; Spinath, Freudenthaler, & Neubauer, 2010; Zhang & Ziegler, 2015). For example, Neuroticism was found to be predictive of grades in Math, Science, and foreign language but not in native language. Similarly, Conscientiousness and Neuroticism were found to be more important for Math performance but Extraversion to be more vital for language learning.

There have been few attempts on building a theory explaining those effects. Mostly, the effects found have been explained as direct consequences of interindividual differences on performance. For example, the effects of Conscientiousness have been explained in terms of motivation to learn (e.g., Colquitt & Simmering, 1998; Komarraju, Karau, & Schmeck, 2009). Conscientiousness reflects a tendency to be purposeful, organized, reliable, determined, and ambitious (Digman, 1990), more conscientious students therefore are believed to be achievement-striving and doing well by working hard. However, considering the level of abstraction of the domains (Ziegler, Danay, Schölmerich, & Bühner, 2010) and the number of facets implicated in the explanations provided so far, it is reasonable to assume that narrower aspects of personality actually build a bridge between the broad traits and performance.

Theoretical Process Model —— B5NT model

One way to integrate and understand the bivariate relationship between the Big Five and scholastic performance is through the analysis level model of personality (Graziano et al., 1997; McAdams, 1995). Build on this model, McAdams and Pals (2006) further integrated and proposed five principles that relate three levels of personality, called "dispositional traits", "characteristic adaptations", and "integrative life narratives". The first level is dispositional traits, which capture "broad individual differences in behavior, thought, and feeling that account for general consistencies across situations and over time" (McAdams & Pals, 2006, p. 212). The second level is characteristic adaptations, which taps "more specific motivational, social-cognitive, and developmental variables that are contextualized in time, situations, and social roles (e.g., goals, values, coping strategies, relational patterns, domain-specific schemas)" (McAdams & Pals, 2006, p. 212). The third level is integrative life narrative, which specifies " internalized and evolving life stories that reconstruct the past and imagine the future to provide a person's life with identity (unity, purpose, meaning)" (McAdams & Pals, 2006, p. 212). It is reasonable to assume that the Big Five domains belong to level 1 and one way they exert their influences on scholastic performance is through strategies and motives positioned on level 2. In a similar vein, Marsh and Craven (2006) proposed a surface-core traits theory, assuming the Big Five to be surface traits and referring to self-concept and other narrower constructs as core personality traits. As such, core traits (learning strategies and motives) are mediating links in the relations of broad traits (the Big Five) and specific behaviors and cognition (see also Caprara, Alessandri, Di Giunta, Panerai, & Eisenberg, 2010).

Figure 1 displays the theoretical model proposed here: the B5NT model (Zhang & Ziegler, under review). It is assumed (a) that students' personality (i.e., the Big Five) will steer them toward the different use of strategies and thereby affects scholastic performance and (b) the Big Five will also provide the motivational impulses or blocks and thereby improve or decrease performance, as well as (c) the mediation effects of learning strategies and self-beliefs (i.e., subject-specific self-concept and self-efficacy) are subject-specific.

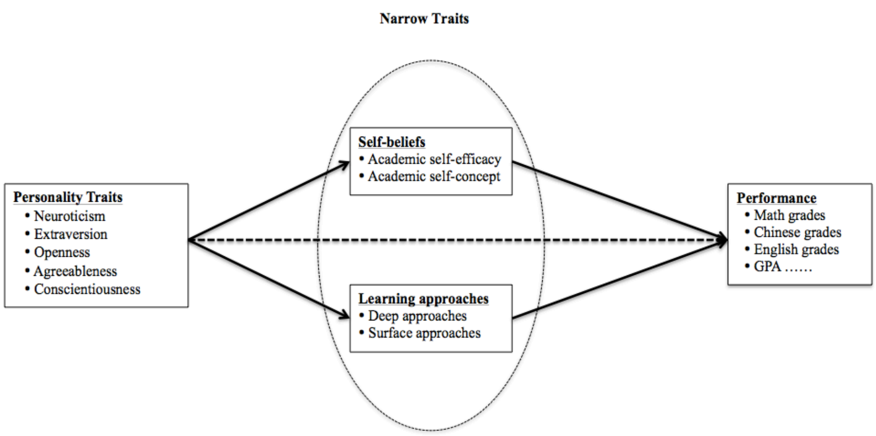


Figure 1. Theoretical process model —— the B5NT model

Prior Empirical Support

Similar to what was found for the Big Five, a body of evidence shows that learning approaches and self-beliefs (i.e., academic self-efficacy and academic self-concept) contribute to the prediction of scholastic performance (e.g., Furnham, Monsen, & Ahmetoglu, 2009; Marsh & Craven, 2006; Pajares, & Schunk, 2001). Moreover, according to McAdams and Pals (2006), learning approaches and self-beliefs belong to the level of characteristic adaptations. If the theoretical approaches outlined are valid, then empirical work should relate the Big Five to specific outcomes via learning approaches and self-beliefs. To date, there is evidence of a mediating role of academic self-efficacy for the relations of Openness and Agreeableness with Math performance (Shams, Mooghali, & Soleimanpour, 2011). In addition, Hair and Graziano (2003) reported a longitudinal mediation effect of self-esteem regarding the relations of Openness and Agreeableness and scholastic performance. Other studies sampled university students and reported the mediating roles of learning approaches (Shokri, Kadivar, Valizadeh, & Sangari, 2007; Swanberg & Martinsen, 2010). In those studies, the influences of Openness and Conscientiousness on scholastic performance were positively mediated by a deep learning approach but negatively by a surface learning approach. In addition, Neuroticism exerted a positive indirect effect on performance through a surface learning approach. A longitudinal study of college students by Corker, Oswald, and Donnelan (2012) found effortful strategies mediated the relationship between Conscientiousness and academic performance.

Unfortunately, past work only looked at self-beliefs and learning approaches as a single mediator separately, which may lead to an overestimation of the mediation effects. Especially when the overlap between the potential mediators is not fully controlled for, the exact processes by which the Big Five affect scholastic performance remain unclear. To address this gap, Zhang and Ziegler (under review) conducted a cross-sectional study and tested the B5NT model to explain why the Big Five affect scholastic performance. Moreover, the investigation examined the mediating roles of learning approaches and self-beliefs simultaneously by the use of a multivariate method with the overlaps among the potential mediators being controlled for. In general, the results supported the idea of the B5NT model, showing that for all subjects (i.e., Math, Chinese, and English), Conscientiousness (positive) and Openness (positive) influenced school grades indirectly through subject-specific self-concept. Additionally, Openness (negative), Neuroticism (positive), and Extraversion (positive) exerted their indirect influences on school grades via a surface learning approach. Moreover, both Conscientiousness and Openness had significant mediation effects on Math and English performance via a deep learning approach. Finally, Neuroticism had a negative mediation effect on Math grades via Math self-concept.

Consequently, there is empirical support for the B5NT model. However, longitudinal support for the proposed mediation processes is missing.

Aim of the Present Study

The main purpose of the present study was to test the B5NT model with learning approaches and self-beliefs as mediating links between the Big Five and scholastic performance. Moreover, the present study overcame the cross-sectional design of previous research by using a three-wave longitudinal panel design covering a time span of 1 year (Dorman & Griffin, 2015). We aimed to examine whether the Big Five at T1 exerted their longitudinal mediation effects on scholastic performance in Math, Chinese, and English at T3 via learning approaches or self-beliefs at T2. Moreover the mediation effects were not only tested between the predictor at T1, the mediator at T2, and the outcomes at T3, but prior levels of all variables were controlled for (Cole & Maxwell, 2003).

Method

Participants and Procedure

The design of this study was a longitudinal cohort survey using questionnaires and school grades in Math, Chinese, and English. Students were surveyed at the beginning of their new academic semester in the school year 2013-2014 (Wave 1), 3 months later (Wave 2), and 9 months after that (Wave 3). The aims of the study and a guarantee of absolute confidentiality were explained to the students. All assessments took place during regular class hours. Participants first had to give some demographic information and then completed a battery of questionnaires. Course grades (Math, Chinese, and English) were collected from the teachers after midterm and endterm examinations. In Wave 1 (T1: February, 2013), a total of 836 (406 girls and 430 boys) secondary school students in the Fujian province of China participated voluntarily in this study. They ranged in age from 11 to 19 (M = 15.35, SD = 1.31) years. In Wave 2 (T2: May, 2013), approximately 8% of the students were no longer in the study, resulting in a total of 769 students who completed the same questionnaires. In Wave 3 (T3: February, 2014), 592 students participated.

Measures

Scholastic performance. Subject-specific performance was operationalized as the course grades of students' midterm and endterm examinations for each subject. Because the midterm and endterm examinations are important tests for school students in China and course grades are the direct form of performance feedback for students. Three or four teachers teaching the same subject in the same grade discussed and prepared the test items before examinations and then marked students' grades anonymously. Therefore, we deemed course grades to be good indicators of scholastic performance. For each subject, grades range from 0 (the worst grade) to 150 (the very best) with lower than 90 indicating insufficient performance.

NEO Five-Factor Inventory (NEO-FFI). The Chinese version of the NEO-FFI was used to measure the Big Five domains, namely Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. It includes 60 items (12 per domain) that are answered on a five-point Likert-type scale ranging from 1 *(totally disagree*) to 5 (*totally agree*). Reliability estimates (Omega: Ω_w, Revelle & Zinbarg, 2009) for each domain were acceptable (.63 to .85) for all three waves and congruent with other Chinese studies involving the questionnaire we used (Yao & Liang, 2010; Yangang, Boxing, & Junqian, 2010).

The Revised Two-Factor Study Process Questionnaire (R-SPQ-2F). This 20-item Chinese revised version of the Study Process Questionnaire was used to assess learning approaches (Biggs, Kember, & Leung, 2001). This measure is composed of two scales assessing deep approach (10 items; Ω_w: .82 to .86) and surface approach (10 items; Ω_w: .73 to .77). Participants had to answer each item on a 1 (*not at all true*) to 5 *(very true*) scale.

Subject-specific Self-efficacy Scale. We assessed subject-specific self-efficacy with a five-item scale for Math, Chinese, and English, respectively (Stankov, Lee, Luo, & Hogan, 2012). An example item is "I am sure I can do difficult work in my Chinese class". Participants were asked to rate the extent to which they agreed or disagreed with each item, using a 1 *(totally disagree*) to 4 (*totally agree*) Likert-type scale. Omega reliability estimates (Ω_w) for each variable obtained in this study were high, ranging from .89 to .93 across three measurement points.

Subject-specific Self-concept Scale. A five-item scale from the Programme for Internal Student Assessment (PISA, 2003) was used to measure Math self-concept. The same items measured self-concept in Chinese and English, respectively (e.g., "I am just not good at Chinese/English"). Participants were asked to evaluate the extent to which they agree or disagree with the verbal descriptors on a four-point Likert-type scale from 1(*totally disagree*) to 4 (*totally agree*). Reliability estimates of each variable obtained for this study are high for all three waves (Ω_w: .89 to .93).

Statistical Analyses Method

In Table A (see Appendix A), the zero-order correlations between all studied variables as estimated using R (R Core Team, 2012) and the psych package (Revelle, 2015) are displayed. Table 1 represents the observed means, standard deviations, mean-level differences, and rank-order stabilities for the Big Five, students' learning approaches and self-beliefs, as well as their school grades in Math, Chinese, and English. These descriptive statistics suggested that there were differences across measurement points. Inspecting the *d*-coefficients, it is apparent that mean-level differences between measurement points were small for all study variables. Looking at the rank-order stability, the different correlations between measurement points are most likely due to different time intervals (i.e., T1-T2: 3 months, T2-T3: 9 months). Second, to test the ideas of the B5NT model for the three school subjects, a structural equation modeling approach (SEM) was used in Mplus 7.2 (Muthén & Muthén, 1998 - 2012). Specifically, a series of three-wave longitudinal mediation models were tested for the three school subjects. Each time only one of the Big Five and one of the narrow traits measured at three measurement points were included. Although our theoretical model is straightforward, we also assessed several competing nested models (see Figure 2) and compared them to one another (Cole & Maxwell, 2003). These models are:

1. Baseline model (M0): This model represents autoregressive effects of within-constructs over time only.
2. Forward causation model (M1): M1 specifies the theoretical B5NT model in which students' personality traits (predictor) predict students' self-beliefs and learning approaches (mediator), which in turn predict school grades (outcome) for both T1-T2 and T2-T3.
3. Reverse causation model (M2): M2 specifies the reverse cross-lagged paths from school grades (predictor) to students' self-beliefs and learning approaches (mediator) to their personality traits (outcome) for both T1-T2 and T2-T3.

4. Reciprocal causation model (M3). This model is M0 with the cross-lagged paths from students' personality traits to their self-beliefs and learning approaches to students' school grades and the other way around.

All models were controlled for age and gender by adding those variables as predictors of variables at T1. Last, we also tested whether the forward or reversed causal pattern is consistent over time by constraining the cross-lagged effects between T1 and T2 to be equal to the same effect between T2 and T3 in a final model M4 (Reciprocal causation model with equal cross-lagged effects). We did so because cross-lagged effects were not expected to change substantially over time.

We assessed the model fit by consulting the chi-square ($\chi2$) test, the Comparative Fit Index (CFI), the Standardized Root Mean Square Residual (SRMR), and the Root Mean Square Error of Approximation (RMSEA) with 90% confidence interval. We accepted that models with CFI values larger than .95, SRMR lower than .08 as long as the upper bound of the RMSEA's 90% confidence interval is .10 or less indicates good fit (Beauducel & Wittmann, 2005; Heene, Hilbert, Draxler, Ziegler, & Bühner, 2011; Hu & Bentler, 1999; Klein, 2011). In addition, chi-square difference tests together with the Akaike information criterion (AIC) were used to compare nested models. As part of the structural analyses, we also tested the significance of longitudinal mediation effects by use of a bootstrap method based on 1,000 samples with 95% confidence intervals (Mallinckrodt, Abraham, Wei, & Russell, 2006; Preacher & Hayes, 2004).

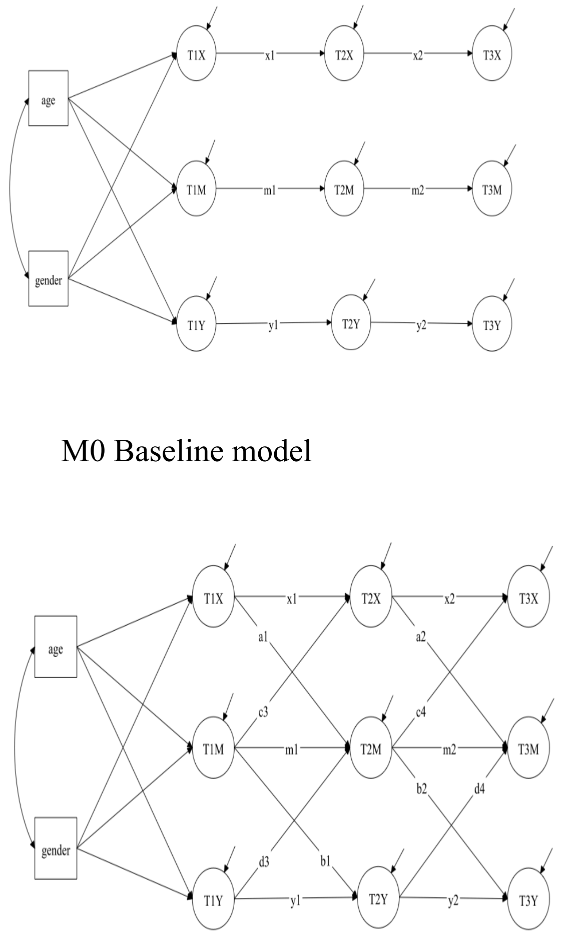
Dealing With Missing Data

It has to be noted that the proportion of missing data for individual items was very low, ranging from 6.6% to 6.9% across the three waves. Further, 14.4% of the grades in Math, 14.7% of the grades in Chinese, as well as 14.7% of the grades in English were missing. These rates of missing data in the school grades were mainly due to the fact that several teachers were not allowed to give out students' course grades. However, these missing data, which were planned, can be considered to be missing completely at random (MCAR; Schafer & Graham, 2002). Moreover, dropout analyses revealed no significant differences at baseline among any of the study variables between those who dropped out and those who did not. Therefore, we decided to deal with missing data by using a full information maximum likelihood procedure.

Table 1. Means, Standard Deviations (SD), Mean-Level Differences, and Rank-Order Stabilities for the Study Variables across T1, T2, and T3.

Variables	*Mean*			*SD*			Effect size			Rank-order stability		
	T1	T2	T3	T1	T2	T3	d_{12}	d_{23}	d_{13}	r_{12}	r_{23}	r_{13}
Neuroticism	35.16	35.11	35.37	7.69	7.86	7.33	-.01	.03	.03	.92	.72	.70
Extraversion	42.28	42.21	42.45	6.43	6.49	6.11	-.01	.04	.03	.91	.70	.68
Openness	41.60	41.83	41.32	5.57	5.62	5.36	.04	-.09	-.05	.90	.68	.63
Agreeableness	29.70	29.81	29.49	5.11	5.28	5.08	.02	-.06	-.04	.83	.62	.61
Conscientiousness	38.34	38.24	39.51	6.25	6.33	6.02	-.02	.21	.19	.90	.70	.65
Deep approach	30.61	30.34	29.46	7.23	7.25	7.47	-.04	-.12	-.16	.89	.68	.59
Surface approach	21.79	21.80	22.41	5.85	5.85	6.15	.00	.10	.10	.88	.59	.55
Math self-concept	13.50	13.57	13.29	3.30	3.31	3.18	.02	-.09	-.07	.93	.83	.80
Math self-efficacy	14.49	14.54	14.08	3.14	3.18	2.99	.02	-.15	-.13	.87	.76	.69
Chinese self-concept	13.95	13.98	14.14	2.98	3.02	3.03	.01	.05	.06	.92	.73	.69
Chinese self-efficacy	13.87	13.95	13.94	3.08	3.17	3.14	.03	.00	.02	.90	.67	.64
English self-concept	13.41	13.41	12.60	3.25	3.34	3.11	.00	-.25	-.26	.92	.92	.72
English self-efficacy	13.58	13.61	12.95	3.46	3.50	3.40	.01	-.19	-.18	.89	.73	.68
Math grades	98.07	96.62	89.01	30.80	32.36	29.14	-.05	-.25	-.30	.79	.71	.62
Chinese grades	101.19	97.93	100.72	20.49	18.87	18.41	-.17	.15	-.02	.72	.75	.74
English grades	100.56	98.78	93.18	32.29	31.86	30.54	-.06	-.18	-.24	.89	.81	.83

Note. N ranges from 455 to 777. We used sum scores for each study variables. *d*-coefficients indicate standardized mean-level differences between measurement points, with positive values representing mean-level increases and negative values indicating mean-level decreases. All stability (correlation) coefficients are significant at $p < .001$. All *P*-values are two-tailed.



M0 Baseline model

M1 Forward causation model

M2 Reverse causation model

M3 Reciprocal causation model

M4 Reciprocal model with equal cross-lagged effects

Figure 2. Different three-wave longitudinal mediation models. *Note.* Three constructs — X, M, and Y — are each measured at three times. In the current study, X refers to the Big Five domains, M stands for the mediators (i.e., deep and surface learning approaches, subject-specific self-beliefs), and Y are school grades in Mathematics, Chinese, and English.

Table 2. Structural equation modeling statistics for a series of three-wave longitudinal mediation models in Math.

Independent Variable	Mediator	Dependent Variable	Model	χ2 (*df*)	RMSEA (90% CI)	CFI	SRMR	*AIC*	*Δχ2 (Δdf)*	
Conscientiousness	Deep approach	Math grade	M0	149.68(33)	.066[.055, .076]	.975	.065	42329.99	M0 vs. M1	24.33 (4), *p* < .05
			M1	125.35(29)	.064[.052, .075]	.979	.042	42313.65	M0 vs. M2	37.45 (4), *p* < .05
			M2	112.23(29)	.059[.048, .071]	.982	.045	42300.53	M1 vs. M3	27.24 (4), *p* < .05
			M3	98.11(25)	.060[.047, .072]	.984	.032	42294.42	M2 vs. M3	14.12 (4), *p* < .05
			M4	**104.51(29)**	**.056[.045, .068]**	**.984**	**.037**	**42292.82**	**M3 vs. M4**	**6.40 (4), *p* > .05**
	Surface approach		M0	131.03(33)	.060[.049, .071]	.976	.046	42083.31	M0 vs. M1	16.85 (4), *p* < .05
			M1	114.18(29)	.060[.048, .071]	.979	.034	42074.46	M0 vs. M2	18.76 (4), *p* < .05
			M2	112.27(29)	.059[.048, .071]	.980	.038	42072.54	M1 vs. M3	17.36 (8), *p* < .05
			M3	96.82(25)	.059[.047, .072]	.983	.030	42065.09	M2 vs. M3	15.45 (4), *p* < .05
			M4	**101.93(29)**	**.055[.044, .067]**	**.982**	**.031**	**42062.21**	**M3 vs. M4**	**5.11 (4), *p* > .05**
	Self-concept		M0	181.88(33)	.074[.064, .085]	.972	.053	38673.00	M0 vs. M1	40.78 (4), *p* < .05
			M1	141.10(29)	.069[.057, .080]	.979	.040	38640.22	M0 vs. M2	33.18 (4), *p* < .05
			M2	148.70(29)	.071[.060, .082]	.977	.040	38647.82	M1 vs. M3	32.45 (4), *p* < .05
			M3	**108.65(25)**	**.064[.052, .076]**	**.984**	**.031**	**38615.77**	M2 vs. M3	40.05 (4), *p* < .05
			M4	139.30(29)	.068[.057, .080]	.979	.034	38638.42	**M3 vs. M4**	**30.65 (4), *p* < .05**
	Self-efficacy		M0	172.41(33)	.072[.061, .082]	.969	.062	39151.00	M0 vs. M1	30.78 (4), *p* < .05
			M1	141.63(29)	.069[.058, .080]	.975	.045	39128.21	M0 vs. M2	36.26 (4), *p* < .05
			M2	136.15(29)	.067[.056, .079]	.976	.044	39122.74	M1 vs. M3	33.32 (4), *p* < .05
			M3	108.31(25)	.064[.052, .076]	.982	.031	39102.89	M2 vs. M3	27.84 (4), *p* < .05
			M4	**115.95(29)**	**.060[.049, .072]**	**.981**	**.033**	**39102.53**	**M3 vs. M4**	**7.64 (4), *p* > .05**
Openness	Deep approach	Math grade	M0	153.10(33)	.066[.056, .077]	.974	.070	42029.75	M0 vs. M1	24.45 (4), *p* < .05
			M1	128.65(29)	.065[.053, .076]	.978	.052	42013.30	M0 vs. M2	19.17 (4), *p* < .05
			M2	133.93(29)	.066[.055, .078]	.977	.056	42018.58	M1 vs. M3	13.68 (4), *p* < .05
			M3	114.97(25)	.066[.054, .079]	.980	.043	42007.61	M2 vs. M3	18.96 (4), p < .05
			M4	**119.30(29)**	**.062[.050, .073]**	**.980**	**.045**	**42003.94**	**M3 vs. M4**	**4.33 (4), *p* > .05**
	Surface approach		M0	135.33(33)	.061[.051, .072]	.975	.061	41657.34	M0 vs. M1	11.33 (4), *p* < .05
			M1	124.00(29)	.063[.052, .075]	.977	.051	41654.01	M0 vs. M2	16.44 (4), *p* < .05
			M2	118.89(29)	.061[.050, .073]	.978	.049	41648.90	M1 vs. M3	16.67 (4), *p* < .05
			M3	**107.33(25)**	**.063[.051, .076]**	**.980**	**.041**	**41645.34**	M2 vs. M3	11.56 (4), *p* < .05
			M4	116.99(29)	.061[.049, .072]	.979	.047	41647.00	**M3 vs. M4**	**9.66 (4), *p* < .05**
	Self-concept		M0	186.44(33)	.075[.065, .086]	.970	.062	38295.19	M0 vs. M1	43.14 (4), *p* < .05

			M1	143.30(29)	.069[.058, .081]	.978	.049	38260.05	M0 vs. M2	23.88 (4), $p < .05$
			M2	162.56(29)	.075[.064, .086]	.974	.051	38279.32	M1 vs. M3	21.63 (4), $p < .05$
			M3	**121.67(25)**	**.069[.057, .081]**	**.981**	**.041**	**38246.42**	M2 vs. M3	40.89 (4), $p < .05$
			M4	150.91(29)	.071[.060, .083]	.977	.044	38267.66	**M3 vs. M4**	**29.24 (4), $p < .05$**
	Self-efficacy		M0	193.74(33)	.077[.067, .088]	.964	.078	38774.74	M0 vs. M1	33.01 (4), $p < .05$
			M1	160.73(29)	.074[.063, .086]	.971	.059	38749.72	M0 vs. M2	47.05 (4), $p < .05$
			M2	146.69(29)	.070[.059, .082]	.974	.055	38735.69	M1 vs. M3	42.43 (4), $p < .05$
			M3	**118.30(25)**	**.067[.055, .080]**	**.979**	**.040**	**38715.30**	M2 vs. M3	28.39 (4), $p < .05$
			M4	139.09(29)	.068[.057, .079]	.976	.048	38728.09	**M3 vs. M4**	**20.79 (4), $p < .05$**
Neuroticism	Deep approach	Math grade	M0	117.09(33)	.056[.045, .067]	.981	.036	43240.59	M0 vs. M1	6.03 (4), $p > .05$
			M1	111.06(29)	.059[.047, .070]	.982	.034	43242.56	M0 vs. M2	4.38 (4), $p > .05$
			M2	112.71(29)	.059[.048, .071]	.982	.034	43244.21	**M1** vs. M3	3.75 (4), $p > .05$
			M3	107.31(25)	.063[.051, .076]	.982	.033	43246.81	**M2** vs. M3	5.40 (4), $p > .05$
			M4	**108.43(29)**	**.058[.046, .069]**	**.982**	**.033**	**43239.94**	**M3 vs. M4**	**1.12 (4), $p > .05$**
	Surface approach		M0	123.13(33)	.058[.047, .069]	.979	.045	42640.44	M0 vs. M1	16.64 (4), $p < .05$
			M1	106.49(29)	.057[.046, .069]	.982	.035	42631.80	M0 vs. M2	8.67 (4), $p > .05$
			M2	114.46(29)	.060[.049, .072]	.980	.039	42639.77	M1 vs. M3	7.27 (4), $p > .05$
			M3	99.22(25)	.060[.048, .073]	.983	.031	42632.53	M2 vs. M3	15.24 (4), $p < .05$
			M4	**106.88(31)**	**.055[.043, .066]**	**.983**	**.035**	**42628.19**	**M3 vs. M4**	**1.77 (4), $p > .05$**
	Self-concept		M0	179.09(33)	.073[.063, .084]	.973	.048	39263.90	M0 vs. M1	48.36 (4), $p < .05$
			M1	130.73(29)	.065[.054, .077]	.981	.035	39223.54	M0 vs. M2	17.50 (4), $p < .05$
			M2	161.59(29)	.075[.064, .086]	.976	.040	39254.40	M1 vs. M3	17.08 (4), $p < .05$
			M3	**113.65(25)**	**.066[.054, .078]**	**.984**	**.031**	**39214.46**	M2 vs. M3	47.94 (4), $p < .05$
			M4	142.18(29)	.069[.058, .080]	.979	.035	39234.99	**M3 vs. M4**	**28.53 (4), $p < .05$**
	Self-efficacy		M0	168.61(33)	.071[.060, .081]	.971	.055	39807.52	M0 vs. M1	29.66 (4), $p < .05$
			M1	138.95(29)	.068[.057, .079]	.976	.041	39785.86	M0 vs. M2	31.10 (4), $p < .05$
			M2	137.51(29)	.067[.056, .079]	.977	.041	39784.42	M1 vs. M3	28.98 (4), $p < .05$
			M3	109.97(25)	.064[.052, .077]	.982	.031	39764.89	M2 vs. M3	27.54 (4), $p < .05$
			M4	**116.22(29)**	**.060[.049, .072]**	**.981**	**.033**	**39763.13**	**M3 vs. M4**	**6.25 (4), $p > .05$**
Agreeableness	Deep approach	Math grade	**M0**	203.88(33)	.079[.069, .090]	.957	.052	42348.96	M0 vs. M1	15.34 (4), $p < .05$
			M1	188.54(29)	.082[.071, .093]	.960	.044	42341.61	M0 vs. M2	42.46 (4), $p < .05$
			M2	161.42(29)	.074[.064, .086]	.966	.043	42314.50	M1 vs. M3	42.93 (4), $p < .05$
			M3	**145.61(25)**	**.077[.065, .089]**	**.969**	**.037**	**42306.69**	M2 vs. M3	15.81 (4), $p < .05$
			M4	171.45(29)	.077[.066, .089]	.964	.045	42324.52	**M3 vs. M4**	**25.84 (4), $p < .05$**
	Surface approach		M0	183.36(33)	.074[.064, .085]	.960	.054	41756.13	M0 vs. M1	16.81 (4), $p < .05$
			M1	166.55(29)	.076[.065, .087]	.963	.044	41747.31	M0 vs. M2	21.77 (4), $p < .05$

			M2	161.59(29)	.075[.064, .086]	.965	.044	41742.35	M1 vs. M3	21.64 (4), $p < .05$
			M3	144.91(25)	.076[.065, .089]	.968	.036	41733.68	M2 vs. M3	16.68 (4), $p < .05$
			M4	**151.15(29)**	**.072[.061, .083]**	**.967**	**.038**	**41731.92**	**M3 vs. M4**	**6.24 (4), $p > .05$**
	Self-concept		M0	242.67(33)	.088[.078, .098]	.956	.057	38421.06	M0 vs. M1	35.50 (4), $p < .05$
			M1	207.17(29)	.086[.076, .098]	.963	.047	38393.56	M0 vs. M2	65.41 (4), $p < .05$
			M2	177.26(29)	.079[.068, .090]	.969	.041	38363.66	M1 vs. M3	68.22 (4), $p < .05$
			M3	**138.95(25)**	**.074[.063, .087]**	**.976**	**.033**	**38333.34**	M2 vs. M3	38.31 (4), $p < .05$
			M4	198.33(29)	.084[.073, .096]	.965	.051	38384.72	**M3 vs. M4**	**59.38 (4), $p < .05$**
	Self-efficacy		M0	252.33(33)	.090[.080, .100]	.946	.069	38940.92	M0 vs. M1	25.00 (4), $p < .05$
			M1	227.33(29)	.091[.080, .102]	.951	.058	38923.92	M0 vs. M2	85.24 (4), $p < .05$
			M2	167.09(29)	.076[.065, .087]	.966	.044	38863.68	M1 vs. M3	87.49 (4), $p < .05$
			M3	**139.84(25)**	**.075[.063, .087]**	**.972**	**.034**	**38844.43**	M2 vs. M3	27.25 (4), $p < .05$
			M4	188.08(29)	.082[.071, .093]	.961	.052	38884.67	**M3 vs. M4**	**48.24 (4), $p < .05$**
Extraversion	Deep approach	Math grade	M0	121.82(33)	.057[.047, .068]	.980	.034	42695.15	**M0** vs. M1	1.81 (4), $p > .05$
			M1	120.01(29)	.062[.051, .073]	.979	.034	42701.34	**M0** vs. M2	5.11 (4), $p > .05$
			M2	116.71(29)	.061[.049, .072]	.980	.033	42698.04	**M1** vs. M3	5.20 (4), $p > .05$
			M3	114.81(25)	.066[.054, .079]	.980	.033	42704.14	**M2** vs. M3	1.90 (4), $p > .05$
			M4	**117.06(29)**	**.061[.049, .072]**	**.980**	**.033**	**42698.39**	**M3 vs. M4**	**2.25 (4), $p > .05$**
	Surface approach		M0	130.67(33)	.060[.049, .071]	.976	.042	42204.56	M0 vs. M1	11.99 (4), $p < .05$
			M1	118.68(29)	.061[.050, .073]	.978	.034	42200.58	M0 vs. M2	7.51 (4), $p > .05$
			M2	123.16(29)	.063[.052, .074]	.977	.037	42205.06	M1 vs. M3	7.48 (4), $p > .05$
			M3	111.20(25)	.065[.053, .077]	.979	.030	42201.09	M2 vs. M3	11.96 (4), $p < .05$
			M4	**119.48(31)**	**.059[.048, .070]**	**.979**	**.034**	**42197.38**	**M3 vs. M4**	**2.41 (4), $p > .05$**
	Self-concept		M0	197.21(33)	.078[.067, .088]	.969	.046	38805.05	M0 vs. M1	46.41 (4), $p < .05$
			M1	150.80(29)	.071[.060, .083]	.977	.036	38766.63	M0 vs. M2	24.00 (4), $p < .05$
			M2	173.21(29)	.078[.067, .089]	.973	.038	38789.04	M1 vs. M3	23.59 (4), $p < .05$
			M3	**127.21(25)**	**.070[.059, .083]**	**.981**	**.031**	**38751.05**	M2 vs. M3	46.00 (4), $p < .05$
			M4	166.74(29)	.076[.065, .087]	.974	.038	38782.57	**M3 vs. M4**	**39.53 (4), $p < .05$**
	Self-efficacy		M0	180.69(33)	.074[.063, .084]	.967	.054	39356.13	M0 vs. M1	22.71 (4), $p < .05$
			M1	157.98(29)	.074[.063, .085]	.971	.042	39341.43	M0 vs. M2	32.02 (4), $p < .05$
			M2	148.67(29)	.071[.060, .082]	.973	.039	39332.11	M1 vs. M3	52.92 (4), $p < .05$
			M3	127.77(25)	.071[.059, .083]	.977	.032	39319.21	M2 vs. M3	20.90 (4), $p < .05$
			M4	**134.39(29)**	**.066[.055, .078]**	**.976**	**.033**	**39317.84**	**M3 vs. M4**	**6.62 (4), $p > .05$**

Note. N = 823. M0 = autoregressive model; M1 = M0 + cross-lagged paths from personality traits to school grades via narrow traits for both T1-T2 and T2-T3; M2 = M0 + reverse cross-lagged effects from school grades to personality traits via narrow traits for both T1-T2 and T2-T3; M3 = M0 + bidirectional cross-lagged effects; M4 = M3 + equality constraints between both cross-lagged effects. The best model for each relationship was boldfaced.

Table 3. Structural equation modeling statistics for a series of three-wave longitudinal mediation models in English.

Independent Variable	Mediator	Dependent Variable	Model	$\chi2$ (*df*)	RMSEA (90% CI)	CFI	SRMR	*AIC*	$\Delta\chi2$ (Δdf)	
Conscientiousness	Deep approach	English grade	M0	242.11(33)	.088[.078, .098]	.961	.067	41762.61	M0 vs. M1	39.60(4), *p* < .05
			M1	202.51(29)	.085[.074, .097]	.968	.041	41731.01	M0 vs. M2	41.46(4), *p* < .05
			M2	200.65(29)	.085[.074, .096]	.968	.043	41729.15	M1 vs. M3	32.74(4), *p* < .05
			M3	169.77(25)	.084[.072, .096]	.973	.024	41706.28	M2 vs. M3	30.88(4), *p* < .05
			M4	**178.66(29)**	**.079[.068, .091]**	**.972**	**.030**	**41707.16**	**M3 vs. M4**	**8.89(4), *p* > .05**
	Surface approach		M0	185.35(33)	.075[.065, .086]	.968	.039	41501.83	M0 vs. M1	12.38(4), *p* < .05
			M1	172.97(29)	.078[.067, .089]	.970	.030	41497.45	M0 vs. M2	12.38(4), *p* < .05
			M2	169.20(29)	.077[.066, .088]	.971	.030	41493.68	M1 vs. M3	28.37(4), *p* < .05
			M3	156.98(25)	.080[.068, .092]	.973	.023	41489.46	M2 vs. M3	12.22(4), *p* < .05
			M4	**163.10(29)**	**.075[.064, .086]**	**.972**	**.026**	**41487.58**	**M3 vs. M4**	**6.12(4), *p* > .05**
	Self-concept		M0	235.21(33)	.086[.076, .097]	.964	.050	38596.76	M0 vs. M1	21.02(4), *p* < .05
			M1	214.19(29)	.088[.077, .099]	.967	.039	38583.74	M0 vs. M2	37.11(4), *p* < .05
			M2	198.10(29)	.084[.073, .095]	.970	.034	38567.65	M1 vs. M3	36.08(4), *p* < .05
			M3	178.11(25)	.086[.075, .098]	.972	.024	38555.66	M2 vs. M3	19.99(4), *p* < .05
			M4	**183.55(29)**	**.080[.070, .092]**	**.972**	**.026**	**38553.10**	**M3 vs. M4**	**5.44(4), *p* > .05**
	Self-efficacy		M0	216.84(33)	.082[.072, .097]	.966	.052	39029.14	M0 vs. M1	23.79(4), *p* < .05
			M1	193.05(29)	.083[.072, .094]	.969	.039	39013.35	M0 vs. M2	38.44(4), *p* < .05
			M2	178.40(29)	.079[.068, .090]	.972	.032	38998.70	M1 vs. M3	36.87(4), *p* < .05
			M3	156.18(25)	.080[.068, .092]	.975	.021	38984.47	M2 vs. M3	22.22(4), *p* < .05
			M4	**161.01(29)**	**.074[.063, .086]**	**.975**	**.022**	**38981.30**	**M3 vs. M4**	**4.83(4), *p* > .05**
Openness	Deep approach	English grade	M0	229.13(33)	.085[.075, .096]	.963	.067	41439.51	M0 vs. M1	44.94(4), *p* < .05
			M1	184.19(29)	.081[.070, .092]	.971	.038	41402.58	M0 vs. M2	23.64(4), *p* < .05
			M2	205.49(29)	.086[.075, .097]	.967	.048	41423.88	M1 vs. M3	15.64(4), *p* < .05
			M3	168.55(25)	.084[.072, .096]	.973	.027	41394.93	M2 vs. M3	36.94(4), *p* < .05
			M4	**176.03(29)**	**.078[.068, .090]**	**.972**	**.029**	**41394.41**	**M3 vs. M4**	**7.48(4), *p* > .05**
	Surface approach		M0	182.85(33)	.074**[.064, .085]**	.969	.047	41045.80	M0 vs. M1	8.53(4), *p* > .05
			M1	174.32(29)	.078[.067, .089]	.970	.039	41045.27	M0 vs. M2	15.19(4), *p* < .05
			M2	167.66(29)	.076[.065, .088]	.971	.032	41038.61	M1 vs. M3	14.38(4), *p* < .05
			M3	159.94(25)	.081[.069, .093]	.972	.026	41038.89	M2 vs. M3	42.43(4), *p* < .05
			M4	**170.18(29)**	**.077[.066, .088]**	**.971**	**.034**	**41041.13**	**M3 vs. M4**	**7.72(4), *p* > .05**
	Self-concept		M0	239.27(33)	.087[.077, .098]	.963	.051	38171.39	M0 vs. M1	22.61(4), *p* < .05

			M1	216.66(29)	.089[.078, .100]	.966	.042	38156.78	M0 vs. M2	39.25(4), *p* < .05
			M2	200.02(29)	.085[.074, .096]	.969	.034	38140.13	M1 vs. M3	36.47(4), *p* < .05
			M3	**180.19(25)**	**.087[.075, .099]**	**.972**	**.029**	**38128.30**	M2 vs. M3	19.83(4), *p* < .05
			M4	191.01(29)	.082[.071, .094]	.971	.032	38131.13	**M3 vs. M4**	**10.91(4), *p* < .05**
	Self-efficacy		M0	223.68(33)	.084[.074, .094]	.964	.056	38624.03	M0 vs. M1	26.04(4), *p* < .05
			M1	197.64(29)	.084[.073, .095]	.968	.042	38605.98	M0 vs. M2	43.13(4), *p* < .05
			M2	180.55(29)	.080[.069, .091]	.971	.035	38588.89	M1 vs. M3	38.15(4), *p* < .05
			M3	**159.49(25)**	**.081[.069, .093]**	**.975**	**.024**	**38575.83**	M2 vs. M3	21.06(4), *p* < .05
			M4	170.74(29)	.077[.066, 088]	.973	.031	38579.09	**M3 vs. M4**	**11.25(4), *p* < .05**
Extraversion	Deep approach	English grade	M0	219.73(33)	.083[.073, .094]	.964	.039	42128.10	M0 vs. M1	20.18(4), *p* < .05
			M1	199.55(29)	.085[.074, .096]	.967	.033	42115.91	M0 vs. M2	11.46(4), *p* < .05
			M2	208.27(29)	.087[.076, .098]	.965	.031	42124.64	M1 vs. M3	10.80(4), *p* < .05
			M3	188.75(25)	.089[.078, .101]	.968	.029	42113.11	M2 vs. M3	19.52(4), *p* < .05
			M4	**194.25(29)**	**.083[.072, .095]**	**.968**	**.030**	**42110.61**	**M3 vs. M4**	**5.50(4), *p* > .05**
	Surface approach		M0	178.81(33)	.073[.063, .084]	.970	.035	41601.90	M0 vs. M1	7.72(4), *p* > .05
			M1	171.09(29)	.077[.066, .089]	.971	.031	41602.18	M0 vs. M2	4.59(4), *p* > .05
			M2	174.22(29)	.078[.067, .089]	.970	.029	41605.32	M1 vs. M3	4.84(4), *p* > .05
			M3	166.25(25)	.083[.071, .095]	.971	.025	41605.35	M2 vs. M3	7.97(4), *p* > .05
			M4	**170.11(29)**	**.077[.066, .088]**	**.971**	**.028**	**41601.22**	**M3 vs. M4**	**3.86(4), *p* > .05**
	Self-concept		M0	235.44(33)	.086[.076, .097]	.964	.048	38640.47	M0 vs. M1	18.26(4), *p* < .05
			M1	217.18(29)	.089[.078, .100]	.967	.040	38630.00	M0 vs. M2	42.32(4), *p* < .05
			M2	193.12(29)	.083[.072, .094]	.971	.028	38605.94	M1 vs. M3	39.52(4), *p* < .05
			M3	177.66(25)	.086[.074, .098]	.973	.023	38598.49	M2 vs. M3	15.46(4), *p* < .05
			M4	**186.44(29)**	**.081[.070, .093]**	**.972**	**.027**	**38599.26**	**M3 vs. M4**	**8.78(4), *p* > .05**
	Self-efficacy		M0	237.64(33)	.087[.077, .097]	.962	.049	39099.98	M0 vs. M1	37.36(4), *p* < .05
			M1	200.28(29)	.085[.074, .096]	.968	.032	39070.61	M0 vs. M2	23.35(4), *p* < .05
			M2	214.29(29)	.088[.077, .099]	.966	.039	39084.62	M1 vs. M3	21.43(4), *p* < .05
			M3	178.85(25)	.086[.075, .099]	.972	.026	39057.18	M2 vs. M3	35.44(4), *p* < .05
			M4	**186.55(29)**	**.081[.070, .093]**	**.971**	**.027**	**39056.89**	**M3 vs. M4**	**7.70(4), *p* > .05**
Neuroticism	Deep approach	English grade	M0	218.10(33)	.083[.072, .093]	.965	.040	42679.77	M0 vs. M1	23.26(4), *p* < .05
			M1	194.84(29)	.083[.072, .095]	.968	.031	42664.51	M0 vs. M2	10.28(4), *p* < .05
			M2	207.82(29)	.087[.076, .098]	.966	.031	42677.48	M1 vs. M3	10.88(4), *p* < .05
			M3	183.96(25)	.088[.076, .100]	.970	.024	42661.63	M2 vs. M3	23.86(4), *p* < .05
			M4	**188.51(29)**	**.082[.071, .093]**	**.970**	**.025**	**42658.18**	**M3 vs. M4**	**4.55(4), *p* > .05**
	Surface approach		M0	180.86(33)	.074[.063, .084]	.971	.037	42045.69	M0 vs. M1	11.76(4), *p* < .05
			M1	169.10(29)	.077[.066, .088]	.972	.029	42041.93	M0 vs. M2	6.23(4), *p* > .05

			M2	174.63(29)	.078[.067, .089]	.971	.029	42047.46	M1 vs. M3	7.02(4), $p > .05$
			M3	162.08(25)	.082[.070, .094]	.973	.022	42042.91	M2 vs. M3	12.55(4), $p < .05$
			M4	**165.55(29)**	**.076[.065, .087]**	**.973**	**.024**	**42038.38**	**M3 vs. M4**	**3.47(4), $p > .05$**
	Self-concept		M0	239.22(33)	.087[.077, .098]	.964	.047	39197.62	M0 vs. M1	17.18(4), $p < .05$
			M1	222.04(29)	.090[.079, .101]	.966	.038	39188.45	M0 vs. M2	39.10(4), $p < .05$
			M2	200.12(29)	.085[.074, .096]	.970	.028	39166.52	M1 vs. M3	37.02(4), $p < .05$
			M3	185.02(25)	.088[.077, .100]	.972	.022	39159.43	M2 vs. M3	15.10(4), $p < .05$
			M4	**191.07(29)**	**.082[.072, .094]**	**.972**	**.025**	**39157.47**	**M3 vs. M4**	**6.05(4), $p > .05$**
	Self-efficacy		M0	229.79(33)	.085[.075, .096]	.964	.048	39676.93	M0 vs. M1	21.87(4), $p < .05$
			M1	207.92(29)	.087[.076, .098]	.967	.037	39663.06	M0 vs. M2	35.95(4), $p < .05$
			M2	193.84(29)	.083[.072, .094]	.970	.029	39648.99	M1 vs. M3	34.44(4), $p < .05$
			M3	173.48(25)	.085[.073, .097]	.973	.021	39636.62	M2 vs. M3	20.36(4), $p < .05$
			M4	**178.38(29)**	**.079[.068, .090]**	**.973**	**.023**	**39633.53**	**M3 vs. M4**	**4.90(4), $p > .05$**
Agreeableness	Deep approach	English grade	M0	283.91(33)	.096[.086, .107]	.946	.053	41774.56	M0 vs. M1	28.96(4), $p < .05$
			M1	254.95(29)	.097[.087, .108]	.951	.042	41753.61	M0 vs. M2	45.06(4), $p < .05$
			M2	238.85(29)	.094[.083, .105]	.955	.040	41737.51	M1 vs. M3	50.44(4), $p < .05$
			M3	**204.51(25)**	**.093[.082, .105]**	**.961**	**.030**	**41711.16**	M2 vs. M3	34.34(4), $p < .05$
			M4	233.45(29)	.093[.082, .104]	.956	.042	41732.10	M3 vs. M4	28.94(4), $p < .05$
	Surface approach		M0	218.31(33)	.083[.072, .093]	.958	.046	41145.10	M0 vs. M1	11.32(4), $p < .05$
			M1	206.99(29)	.086[.075, .098]	.960	.038	41141.79	M0 vs. M2	20.92(4), $p < .05$
			M2	197.39(29)	.084[.073, .095]	.962	.035	41132.19	M1 vs. M3	22.12(4), $p < .05$
			M3	184.87(25)	.088[.076, .100]	.964	.029	41127.66	M2 vs. M3	12.52(4), $p < .05$
			M4	**193.39(29)**	**.083[.072, .094]**	**.963**	**.033**	**41128.18**	**M3 vs. M4**	**8.52(4), $p > .05$**
	Self-concept		M0	267.15(33)	.093[.083, .103]	.954	.052	38304.45	M0 vs. M1	17.08(4), $p < .05$
			M1	250.07(29)	.096[.085, .107]	.957	.045	38295.38	M0 vs. M2	52.09(4), $p < .05$
			M2	215.06(29)	.088[.077, .100]	.964	.031	38260.36	M1 vs. M3	51.87(4), $p < .05$
			M3	**198.20(25)**	**.092[.080, .104]**	**.966**	**.026**	**38251.51**	M2 vs. M3	16.86(4), $p < .05$
			M4	217.31(29)	.089[.078, .100]	.963	.038	38262.61	**M3 vs. M4**	**19.11(4), $p < .05$**
	Self-efficacy		M0	255.21(33)	.090[.080, .101]	.954	.053	38779.26	M0 vs. M1	22.58(4), $p < .05$
			M1	232.63(29)	.092[.082, .104]	.958	.043	38764.68	M0 vs. M2	44.83(4), $p < .05$
			M2	210.38(29)	.087[.076, .098]	.963	.033	38742.43	M1 vs. M3	45.50(4), $p < .05$
			M3	**187.13(25)**	**.089[.077, .101]**	**.966**	**.027**	**38727.17**	M2 vs. M3	23.25(4), $p < .05$
			M4	199.88(29)	.085[.074, .096]	.965	.036	38731.93	**M3 vs. M4**	**12.75(4), $p < .05$**

Note. N = 823. M0 = autoregressive model; M1 = M0 + cross-lagged paths from personality traits to school grades via narrow traits for both T1-T2 and T2-T3; M2 = M0 + reverse cross-lagged effects from school grades to personality traits via narrow traits for both T1-T2 and T2-T3; M3 = M0 + bidirectional cross-lagged effects; M4 = M3 + equality constraints between both cross-lagged effects. The best model for each relationship was boldfaced.

Table 4. Structural equation modeling statistics for a series of three-wave longitudinal mediation models in Chinese.

Independent Variable	Mediator	Dependent Variable	Model	χ2 (*df*)	RMSEA (90% CI)	CFI	SRMR	*AIC*	*Δχ2 (Δdf)*	
Conscientiousness	Deep approach	Chinese grades	M0	263.00(33)	.092[.082, .103]	.951	.070	40406.29	M0 vs. M1	41.84 (4), *p* < .05
			M1	221.16(29)	.090[.079, .101]	.959	.047	40372.46	M0 vs. M2	40.87 (4), *p* < .05
			M2	222.13(29)	.090[.079, .101]	.958	.053	40373.42	M1 vs. M3	30.31 (4), *p* < .05
			M3	**190.85(25)**	**.090[.078, .102]**	**.964**	**.039**	**40350.14**	M2 vs. M3	31.28 (4), *p* < .05
			M4	210.43(29)	.087[.076, .098]	.961	.043	40361.73	**M3 vs. M4**	**19.58 (4), *p* < .05**
	Surface approach		M0	210.18(33)	.081[.071, .091]	.957	.051	40154.98	M0 vs. M1	18.28 (4), *p* < .05
			M1	191.90(29)	.083[.072, .094]	.960	.040	40144.70	M0 vs. M2	15.42 (4), *p* < .05
			M2	194.76(29)	.083[.072, .095]	.959	.047	40147.57	M1 vs. M3	14.82 (4), *p* < .05
			M3	177.08(25)	.086[.074, .098]	.963	.037	40137.88	M2 vs. M3	17.68 (4), *p* < .05
			M4	**183.64(29)**	**.080[.070, .092]**	**.962**	**.039**	**40136.44**	**M3 vs.M4**	**6.56 (4), *p* > .05**
	Self-concept		M0	210.82(33)	.081[.071, .092]	.962	.049	37095.10	M0 vs. M1	8.88 (4), *p* > .05
			M1	201.94(29)	.085[.074, .096]	.963	.043	37094.22	M0 vs. M2	13.16 (4), *p* < .05
			M2	197.66(29)	.084[.073, .095]	.964	.044	37089.94	M1 vs. M3	13.06 (4), *p* < .05
			M3	188.88(25)	.089[.078, .101]	.965	.040	37089.16	M2 vs. M3	8.78 (4), *p* > .05
			M4	**197.17(29)**	**.084[.073, .095]**	**.964**	**.043**	**37089.45**	**M3 vs. M4**	**8.29 (4), *p* > .05**
	Self-efficacy		M0	212.66(33)	.081[.071, .092]	.959	.052	37457.77	M0 vs. M1	8.48 (4), *p* > .05
			M1	204.18(29)	.086[.075, .097]	.960	.046	37457.28	M0 vs. M2	13.61 (4), *p* < .05
			M2	199.05(29)	.084[.074, .096]	.961	.045	37452.15	M1 vs. M3	13.36 (4), *p* < .05
			M3	190.82(25)	.090[.078, .102]	.962	.040	37451.92	M2 vs. M3	8.23 (4), *p* > .05
			M4	**199.25(29)**	**.084[.074, .096]**	**.961**	**.043**	**37452.35**	**M3 vs. M4**	**8.43 (4), *p* > .05**
Openness	Deep approach	Chinese grades	M0	260.70(33)	.092[.081, .102]	.950	.071	40091.98	M0 vs. M1	44.65 (4), *p* < .05
			M1	216.05(29)	.089[.078, .100]	.959	.048	40055.34	M0 vs. M2	24.51 (4), *p* < .05
			M2	236.19(29)	.093[.082, .104]	.954	.059	40075.47	M1 vs. M3	17.14 (4), *p* < .05
			M3	**198.91(25)**	**.092[.080, .104]**	**.962**	**.043**	**40046.19**	M2 vs. M3	37.28 (4), *p* < .05
			M4	217.71(29)	.089[.078, .100]	.958	.044	40056.99	**M3 vs. M4**	**18.80 (4), *p* > .05**
	Surface approach		M0	207.19(33)	.080[.070, .091]	.957	.058	39713.82	M0 vs. M1	13.99 (4), *p* < .05
			M1	193.20(29)	.083[.072, .094]	.960	.048	39707.83	M0 vs. M2	14.20 (4), *p* < .05
			M2	192.99(29)	.083[.072, .094]	.960	.050	39707.62	M1 vs. M3	13.70 (4), *p* < .05
			M3	179.50(25)	.087[.075, .099]	.962	.041	39702.13	M2 vs. M3	13.49 (4), *p* < .05
			M4	**190.71(29)**	**.082[.071, .094]**	**.960**	**.045**	**39705.35**	**M3 vs. M4**	**11.21 (4), *p* < .05**
	Self-concept		M0	210.81(33)	.081[.071, .092]	.962	.054	36646.71	M0 vs. M1	9.22 (4), *p* > .05

			M1	201.59(29)	.085[.074, .096]	.963	.047	36645.49	M0 vs. M2	9.01 (4), $p > .05$
			M2	201.80(29)	.085[.074, .096]	.963	.050	36645.69	M1 vs. M3	9.35 (4), $p < .05$
			M3	**192.24(25)**	**.090[.079, .102]**	**.964**	**.044**	**36644.14**	M2 vs. M3	9.56 (4), $p < .05$
			M4	203.19(29)	.085[.075, .097]	.962	.049	36647.08	**M3 vs. M4**	**10.95 (4), $p < .05$**
	Self-efficacy		M0	213.53(33)	.082[.071, .092]	.958	.055	37056.41	M0 vs. M1	9.86 (4), $p < .05$
			M1	203.67(29)	.086[.075, .097]	.960	.048	37054.55	M0 vs. M2	10.24 (4), $p < .05$
			M2	203.29(29)	.085[.075, .097]	.960	.050	37054.17	M1 vs. M3	8.86 (4), $p > .05$
			M3	194.81(25)	.091[.079, .103]	.961	.044	37053.69	M2 vs. M3	8.48 (4), $p > .05$
			M4	**208.68(29)**	**.087[.076, .098]**	**.959**	**.049**	**37059.56**	**M3 vs. M4**	**13.87 (4), $p < .05$**
Neuroticism	Deep approach	Chinese grades	M0	238.74(33)	.087[.077, .098]	.954	.048	41320.54	M0 vs. M1	23.79 (4), $p < .05$
			M1	214.95(29)	.088[.077, .100]	.959	.041	41304.75	M0 vs. M2	8.83 (4), $p > .05$
			M2	229.91(29)	.092[.081, .103]	.955	.046	41319.71	M1 vs. M3	8.51 (4), $p > .05$
			M3	**206.44(25)**	**.094[.082, .106]**	**.960**	**.040**	**41304.24**	M2 vs. M3	23.47 (4), $p < .05$
			M4	221.74(29)	.090[.079, .101]	.957	.040	41311.54	**M3 vs. M4**	**15.30 (4), $p < .05$**
	Surface approach		M0	207.59(33)	.080[.070, .091]	.959	.049	40702.95	M0 vs. M1	17.41 (4), $p < .05$
			M1	190.18(29)	.082[.071, .093]	.963	.039	40693.55	M0 vs. M2	4.73 (4), $p > .05$
			M2	202.86(29)	.085[.074, .097]	.960	.045	40706.22	M1 vs. M3	4.75 (4), $p > .05$
			M3	185.43(25)	.088[.077, .100]	.963	.037	40696.79	M2 vs. M3	17.43 (4), $p < .05$
			M4	**189.21(29)**	**.082[.071, .093]**	**.963**	**.038**	**40692.58**	**M3 vs. M4**	**3.78 (4), $p > .05$**
	Self-concept		M0	206.64(33)	.080[.070, .091]	.964	.043	37664.69	M0 vs. M1	7.89 (4), $p > .05$
			M1	198.75(29)	.084[.073, .096]	.965	.039	37664.81	M0 vs. M2	4.98 (4), $p > .05$
			M2	201.66(29)	.085[.074, .096]	.964	.042	37667.72	M1 vs. M3	5.35 (4), $p > .05$
			M3	193.40(25)	.090[.079, .103]	.965	.038	37667.46	M2 vs. M3	8.26 (4), $p > .05$
			M4	**201.05(29)**	**.085[.074, .096]**	**.964**	**.041**	**37667.11**	**M3 vs. M4**	**7.65 (4), $p > .05$**
	Self-efficacy		M0	209.27(33)	.081[.070, .091]	.961	.046	38099.11	M0 vs. M1	6.38 (4), $p > .05$
			M1	202.89(29)	.085[.074, .097]	.962	.042	38100.73	M0 vs. M2	6.40 (4), $p > .05$
			M2	202.87(29)	.085[.074, .097]	.962	.042	38100.71	M1 vs. M3	6.28 (4), $p < .05$
			M3	196.61(25)	.091[.080, .103]	.962	.039	38102.45	M2 vs. M3	6.26 (4), $p < .05$
			M4	**203.15(29)**	**.085[.075, .097]**	**.961**	**.042**	**38100.99**	**M3 vs. M4**	**6.54 (4), $p > .05$**
Extraversion	Deep approach	Chinese grades	M0	260.12(33)	.091[.081, .102]	.949	.049	40758.36	M0 vs. M1	20.79 (4), $p < .05$
			M1	239.33(29)	.094[.083, .105]	.952	.042	40745.57	M0 vs. M2	10.90 (4), $p < .05$
			M2	249.22(29)	.096[.085, .107]	.950	.047	40755.46	M1 vs. M3	10.17 (4), $p < .05$
			M3	**229.16(25)**	**.100[.088, .112]**	**.954**	**.042**	**40743.39**	M2 vs. M3	20.06 (4), $p < .05$
			M4	245.06(29)	.095[.084, .106]	.951	.043	40751.29	**M3 vs. M4**	**15.90 (4), $p < .05$**
	Surface approach		M0	221.13(33)	.101[.088, .114]	.954	.049	40250.22	M0 vs. M1	12.86 (4), $p < .05$
			M1	208.27(29)	.087[.076, .098]	.956	.041	40245.36	M0 vs. M2	3.33 (4), $p > .05$

			M2	217.80(29)	.089[.078, .100]	.954	.047	40254.88	M1 vs. M3	3.92 (4), $p > .05$
			M3	204.35(25)	.093[.082, .105]	.956	.040	40249.44	M2 vs. M3	13.45 (4), $p < .05$
			M4	**208.68(29)**	**.087[.076, .098]**	**.956**	**.041**	**40245.76**	**M3 vs. M4**	**4.33 (4), $p > .05$**
	Self-concept		M0	225.64(33)	.084[.074, .095]	.959	.044	37154.04	M0 vs. M1	5.67 (4), $p > .05$
			M1	219.97(29)	.089[.079, .101]	.959	.042	37156.36	M0 vs. M2	6.86 (4), $p > .05$
			M2	218.78(29)	.089[.078, .100]	.960	.044	37155.17	M1 vs. M3	7.37 (4), $p > .05$
			M3	212.60(25)	.095[.084, .108]	.960	.042	37157.00	M2 vs. M3	6.18 (4), $p > .05$
			M4	**220.90(29)**	**.090[.079, .101]**	**.959**	**.044**	**37157.30**	**M3 vs. M4**	**8.30 (4), $p > .05$**
	Self-efficacy		M0	229.15(33)	.085[.075, .096]	.956	.050	37564.68	M0 vs. M1	7.94 (4), $p > .05$
			M1	221.21(29)	.090[.079, .101]	.956	.045	37564.74	M0 vs. M2	7.11 (4), $p > .05$
			M2	222.04(29)	.090[.079, .101]	.956	.045	37565.57	M1 vs. M3	6.21 (4), $p < .05$
			M3	215.00(25)	.096[.084, .108]	.957	.042	37566.53	M2 vs. M3	7.04 (4), $p < .05$
			M4	**224.27(29)**	**.090[.080, .102]**	**.956**	**.046**	**37567.80**	**M3 vs. M4**	**9.27 (4), $p > .05$**
Agreeableness	Deep approach	Chinese grades	M0	305.22(33)	.100[.090, .111]	.930	.059	40428.61	M0 vs. M1	34.53 (4), $p < .05$
			M1	270.69(29)	.101[.090, .112]	.938	.048	40402.07	M0 vs. M2	48.63 (4), $p < .05$
			M2	256.59(29)	.098[.087, .109]	.941	.051	40387.98	M1 vs. M3	46.06 (4), $p < .05$
			M3	**224.63(25)**	**.099[.087, .111]**	**.949**	**.042**	**40364.01**	M2 vs. M3	31.96 (4), $p < .05$
			M4	264.44(29)	.099[.089, .110]	.939	.050	40395.83	**M3 vs. M4**	**39.81 (4), $p < .05$**
	Surface approach		M0	243.47(33)	.088[.078, .099]	.943	.055	39815.48	M0 vs. M1	18.52 (4), $p < .05$
			M1	224.95(29)	.091[.080, .102]	.947	.044	39804.96	M0 vs. M2	20.49 (4), $p < .05$
			M2	222.98(29)	.090[.079, .101]	.947	.048	39802.99	M1 vs. M3	19.45 (4), $p < .05$
			M3	205.50(25)	.094[.082, .106]	.951	.039	39793.51	M2 vs. M3	20.79 (4), $p < .05$
			M4	**213.46(29)**	**.088[.077, .099]**	**.950**	**.041**	**39793.47**	**M3 vs. M4**	**7.96 (4), $p > .05$**
	Self-concept		M0	238.54(33)	.087[.077, .098]	.951	.049	36807.50	M0 vs. M1	17.48 (4), $p < .05$
			M1	226.29(29)	.091[.080, .102]	.953	.044	36803.24	M0 vs. M2	9.44 (4), $p > .05$
			M2	229.10(29)	.092[.081, .103]	.952	.046	36806.06	M1 vs. M3	9.51 (4), $p < .05$
			M3	216.78(25)	.097[.085, .109]	.954	.041	36801.74	M2 vs. M3	9.51 (4), $p < .05$
			M4	**224.95(29)**	**.091[.080, .102]**	**.953**	**.044**	**36801.91**	**M3 vs. M4**	**8.17 (4), $p > .05$**
	Self-efficacy		M0	248.03(33)	.089[.079, .100]	.945	.049	37210.73	M0 vs. M1	7.12 (4), $p > .05$
			M1	240.91(29)	.094[.083, .105]	.945	.045	37211.60	M0 vs. M2	11.93 (4), $p < .05$
			M2	236.10(29)	.093[.082, .104]	.947	.045	37206.80	M1 vs. M3	11.48 (4), $p < .05$
			M3	229.43(25)	.100[.088, .112]	.947	.042	37208.12	M2 vs. M3	6.67 (4), $p > .05$
			M4	**237.26(29)**	**.093[.083, .105]**	**.946**	**.045**	**37207.96**	**M3 vs. M4**	**7.83 (4), $p > .05$**

Note. N = 823. M0 = autoregressive model; M1 = M0 + cross-lagged paths from personality traits to school grades via narrow traits for both T1-T2 and T2-T3; M2 = M0 + reverse cross-lagged effects from school grades to personality traits via narrow traits for both T1-T2 and T2-T3; M3 = M0 + bidirectional cross-lagged effects; M4 = M3 + equality constraints between both cross-lagged effects. The best model for each relationship was boldfaced.

Results

Model Evaluation

Altogether we tested 300 models (5 personality traits * 5 models * 4 mediators * 3 school subjects). As expected, all the models fitted the data reasonably well (see Table 2-4). A series of chi-square differences tests together with AICs suggest that in most cases, the model assuming equal cross-lagged effects fitted the best. Even though, in very few cases, the model with unequal cross-lagged effects fitted the data slightly better than the one with equal cross-lagged effects, there were always suppression effects (Cohen, Cohen, West, & Aiken, 1983). Therefore, in terms of parsimony, we decided to continue the longitudinal mediation analyses by setting the cross-lagged effects between variables to be equal (M4).

Longitudinal Mediation Effects

Table 5 shows all significant longitudinal mediation effects and the associated 95% confidence intervals based on 1,000 bootstrap samples. Specifically, both T1 Conscientiousness (positive) and T1 Neuroticism (negative) had a significant mediation effect on T3 school grades for all three subjects, via T2 surface learning approaches. In addition, T1 Openness (positive), T1 Conscientiousness (positive), and T1 Agreeableness (negative) had a mediation effect on T3 school grades via T2 deep learning approaches but only for English and Chinese. In the case of English, T1 Neuroticism also had a negative mediation effect on T3 English grades via T2 deep learning approaches, and T1 Conscientiousness had a positive mediation effect on T3 English grades through T2 English self-concept. For Math, T1 Openness (positive) and T1 Neuroticism (negative) had a mediation effect on T3 Math grades via T2 Math self-efficacy and T2 Math self-concept. Additionally, T1 Conscientiousness (positive) and T1 Agreeableness (negative) had a mediation effect on T3 Math grades via T2 Math self-efficacy but not Math self-concept.

Notably, very limited support was found for the reverse paths from T1 school grades to T3 personality via T2 narrow traits. Specifically, Math grades at T1 had a mediation effect on Agreeableness and Conscientiousness at T3 via Math self-efficacy at T2. In addition, English grades at T1 had a mediation effect on Agreeableness at T3 via English self-efficacy at T2.

Table 5. Standardized Estimates and Bias-Corrected Confidence Intervals for Specific Mediation Effects in Mathematics, English, and Chinese.

	Longitudinal mediation effects								
	Math			English			Chinese		
Path	*b*	*SE*	95% CI	*b*	*SE*	95% CI	*b*	*SE*	95% CI
T1Conscientiousness-T2 Deep approach-T3 Grades	.004	.006	[-.005, .017]	**.016**	**.007**	**[.006, .035]**	**.007**	**.004**	**[.001, .019]**
T1Conscientiousness-T2 Surface approach-T3 Grades	**.010**	**.007**	**[.001, .029]**	**.007**	**.004**	**[.000, .017]**	**.008**	**.005**	**[.001, .019]**
T1Conscientiousness-T2 Self-concept-T3 Grades	.009	.006	[-.001, .023]	**.010**	**.005**	**[.001, .022]**	.002	.002	[-.001, .007]
T1Conscientiousness-T2 Self-efficacy-T3 Grades	**.016**	**.008**	**[.004, .035]**	.007	.006	[-.003, .023]	.002	.002	[-.001, .008]
T1Openness-T2 Deep approach-T3 Grades	.006	.008	[-.009, .022]	**.025**	**.009**	**[.012, .049]**	**.011**	**.007**	**[.001, .028]**
T1Openness-T2 Self-concept-T3 Grades	**.013**	**.007**	**[.002, .029]**	< .001	.001	[-.008, .012]	.002	.002	[-.001, .010]
T1Openness-T2 Self-efficacy-T3 Grades	**.015**	**.008**	**[.002, .036]**	.001	.001	[-.003, .019]	.001	.003	[-.002, .009]
T1Neuroticism-T2 Deep approach-T3 Grades	-.002	.003	[-.010, .002]	**-.002**	**.001**	**[-.017, -.001]**	-.003	.003	[-.010, .000]
T1Neuroticism-T2 Surface approach-T3 Grades	**-.008**	**.005**	**[-.021, -.001]**	**-.001**	**.001**	**[-.014, -.001]**	**-.006**	**.003**	**[-.014, -.001]**
T1Neuroticism-T2 Self-concept-T3 Grades	**-.014**	**.005**	**[-.026, -.005]**	< .001	.001	[-.009, .006]	-.001	.002	[-.007, .001]
T1Neuroticism-T2 Self-efficacy-T3 Grades	**-.013**	**.005**	**[-.026, -.004]**	< .001	.001	[-.011, .006]	< .001	.002	[-.003, .004]
T1Agreeableness-T2 Deep approach-T3Grades	-.004	.006	[-.017, .007]	**-.003**	**.001**	**[-.036, -.008]**	**-.008**	**.005**	**[-.021, -.001]**
T1Agreeableness-T2 Self-efficacy -T3Grades	**-.013**	**.008**	**[-.033, -.002]**	-.001	.001	[-.024, .004]	-.001	.002	[-.007, .003]
T1 Grades -T2 Self-efficacy -T3 Agreeableness	**-.008**	**.002**	**[-.012, -.003]**	**-.004**	**.002**	**[-.002, .000]**	< .001	< .001	[-.001, .001]
T1 Grades -T2 Self-efficacy -T3 Conscientiousness	**.003**	**.002**	**[.000, .007]**	.003	.002	[-.001, .006]	< .001	.001	[-.001, .001]

Note. A series of structural equation models were conducted for each Big Five domains, each of narrow traits, and each school subject. For clarity reasons, we only displayed the models with significant longitudinal mediation effects.

Additional Findings

Reciprocal effects of narrow traits on the Big Five domains. After controlling for age and gender, reciprocal effects of deep learning approaches on Openness, Conscientiousness, and Agreeableness for both T1-T2 and T2-T3 were significant and stable. Deep learning approaches at T1 significantly predicted Openness, Conscientiousness, and Agreeableness at T2 (ßs = .05, .08, and -.08, $p < .05$, respectively), and deep learning approach at T2 also significantly predicted Openness, Conscientiousness, and Agreeableness at T3 (ßs = .05, .08, and -.08, $p < .05$, respectively). In addition, T1 surface learning approaches predicted T2 Conscientiousness (ß = -.04, $p < .05$), and T2 surface learning approaches also predicted T3 Conscientiousness (ß = -.05, $p < .05$).

Reciprocal effects of school grades on narrow traits. For Math and English, reciprocal effects of school grades on subject-specific self-efficacy and subject-specific self-concept were also significant. That is, Math and English grades at T1 predicted the corresponding self-efficacy at T2 (ßs = .08 and .09, $p < .05$, respectively), and self-concept at T2 (ßs = .03 and .08, $p < .05$, respectively). Also, Math and English grades at T2 predicted the corresponding self-efficacy at T3 (ßs = .10 and .09, $p < .05$, respectively) and self-concept at T3 (ßs = .04 and .09, $p < .05$, respectively). For English and Chinese, reciprocal effects of school grades on deep learning approaches were also significant. Specifically, English and Chinese grades at T1 predicted a deep learning approach at T2 (ßs = .05 and .04, $p < .05$, respectively), and T2 English and Chinese grades also predicted T3 deep learning approaches (ßs = .05 and .04, $p < .05$, respectively). In contrast, T1 Math grades significantly but negatively predicted T2 surface-learning approaches (ß = -.04, $p < .05$), and T2 Math grades predicted T3 surface-learning approaches (ß = -.04, $p < .05$).

Discussion

Based on the analysis level model of personality perspective (Graziano et al., 1997; McAdams, 1995) and Marsh and Craven's (2006) surface-core traits theory, the present study tested the B5NT model to explain the influences of the Big Five on scholastic performance. In contrast to most prior studies, the present study employed SEM on the data resulting from a three-wave longitudinal study among a large sample of Chinese secondary school students. Our specific findings did not completely replicate the findings derived from our previous cross-sectional study, which underscored the necessity of conducting a longitudinal study. Nevertheless, the results confirm the ideas of the B5NT model in general. Additionally, empirical support suggesting an extension of the model was found with specific feedbacks from narrow traits to broad traits and performance to narrow traits.

Longitudinal Indirect Effects——the B5NT Model

In line with our expectations, the findings confirm and extend previous cross-sectional (Chamorro-Premuzic & Furnham, 2008; Furnham & Monsen, 2009; Zhang & Ziegler, 2015), meta-analytic (O'Connor & Paunonen, 2007; Poropat, 2009; Richardson et al., 2012), and longitudinal findings (Chamorro-Premuzic & Furnham, 2003; Martin, Montgomery, & Saphian, 2006; Noftle & Robins, 2007) that the Big Five contribute to scholastic performance. More importantly, our findings are encouraging as we found strong support for the longitudinal mediation effects of learning approaches and self-beliefs. To my best knowledge, this study is one of the first to consider the longitudinal mediation effects of both self-beliefs and learning strategies over time in a three-wave panel design. Our findings suggest that certain personality traits predict scholastic performance over time indirectly via narrow traits. Moreover, except for several cross-subject indirect effects, it was shown that some of these mechanisms are subject-specific.

Cross-subject longitudinal indirect effects. After controlling for age and gender, Conscientiousness (positive) and Neuroticism (negative) at T1 were significantly associated with a surface learning approach at T2, which in turn, were negatively associated with school grades at T3 for all three subjects. Conscientious students are believed to be achievement striving and obligation oriented. It is not surprising that students who are less conscientious tend to seek only a reproduction of what is taught to meet the minimum requirement (surface learning approaches) rather than a real understanding of what is learned (deep learning approaches). In contrast, students scoring high Neuroticism are inclined to experience higher level of anxiety and be afraid of failing in the examination. Thus, they might pay more attention to not failing than fully understanding.

Subject-specific longitudinal indirect effects. Regarding the mediating roles of learning approaches, subject-specific effects were observed in language subjects. For language subjects, Openness (positive), Conscientiousness (positive), and Agreeableness (negative) at T1 were significantly related to a deep learning approach at T2, which in turn was positively related to scholastic performance at T3. On the one hand, it is reasonable that more open and more conscientious students really want to understand what they have learnt and are highly motivated to utilize more deep learning approaches to achieve their goals. As for Agreeableness, it is a little surprising that more agreeable students tend to use less deep learning approaches to solve their school tasks. This can be due to the fact that Chinese students prefer learning by their own rather than cooperation in a group. Doing so might help them to concentrate on the tasks better and motivate them to adopt more deep learning approaches. On the other hand, language learning, in particular students' mother language learning, emphasizes reading comprehension and writing which require deep understanding and flexible application of what is learned (deep learning approaches). Of note, specifically for English, we also found that Neuroticism at T1 had a negative indirect effect on English grades at T3 via a deep learning approach at T2. One possible explanation might be related to the specific characteristics of English subject. For Chinese students, English is a totally new language system with new alphabets and different grammar rules. Moreover, as is the case for Chinese and Mathematics, English is one of the main compulsory subjects in the secondary school. English grades therefore have a direct impact on opportunities to pursue a higher level of education. Therefore, students tend to be afraid of their performance in English and experience higher levels of anxiety, all of which might lead to using less of a deep learning approaches to solve tasks.

With regard to the mediating roles of self-beliefs, most subject-specific effects were observed in Math. It is suggested that more open and less neurotic students tend to develop more positive self-beliefs in their Math learning, which help them to achieve higher Math performance. Our findings not only replicated prior cross-sectional (Shams et al., 2011) and longitudinal findings (Hair & Graziano, 2003; Noftle & Robins, 2007), but also extend them to different subjects and different culture. Interestingly, we did find Agreeableness had a longitudinal indirect effect on Math performance via Math self-efficacy but functioned in a negative way. As mentioned, one explanation could be due to the fact that Chinese students prefer studying independently instead of in a group. In this way, they may concentrate on the tasks better and think deeply, all of which might help them to acquire deep learning approaches, thereby improving their performance. Furthermore, successful performance in their learning as an internal reward might motivate them to formulate more positive self-perception in their Math learning, thereby increasing their performance. For Conscientiousness, we found a longitudinal indirect effect on Math grades via Math self-efficacy and on English grades via English self-concept, as consistent with Levpušček, Zupančič, and Sočan (2012). The findings are in line with the basic definition of Conscientiousness (Digman, 1990). It is suggest that conscientious students with their persistence, effective study habits, and willingness to put effort into learning, may have advantages in developing positive beliefs in their learning, which in turn improves their achievement.

Taken together, it seems that deep learning approaches are more important for English and Chinese learning while self-beliefs are more vital for Math and English learning. The different patterns of results for different subjects may be related to how students learn Math in comparison with language subjects and how students learn Chinese (i.e., mother language) in comparison to English (i.e., foreign language). In general, the results for language subjects (i.e., Chinese and English) were relatively consistent, with only a few slightly different findings. Whereas Chinese is the students' native language with a much higher degree of familiarity, English is a very new language system with a new alphabet and new vocabulary. In the Chinese education system, reading comprehension and writing are highly emphasized in language learning, which demand students' deep understanding and flexible application of what they have learnt. Contrary to language subjects, Mathematics seems to be more difficult for students and is more strongly associated with cognitive challenges and problem solving. As such, higher self-beliefs might be required to keep up students' efforts invested into solving mathematic problems. In combination, all of this might explain why the longitudinal indirect effects of a deep learning approach in the relations of Openness and Conscientiousness could be observed in language subjects but disappeared in Math, compared to the cross-sectional study (Zhang & Ziegler, under review). It appears that in the short-term run, a deep learning approach might be useful for students to solve a variety of Mathematics problems, but in the long-term run, students' self-beliefs in Math learning might be more advantageous in keeping up students' efforts.

Additional Findings —— Reciprocal Effects

Our three-wave panel study also allowed for the test of reciprocal effects producing interesting findings: for Math and English, there was a small and positive mutual influence between students' scholastic performance and their corresponding self-efficacy and self-concept. These reciprocal effects occurred through the whole school year and were stable over time. In general, our findings offered direct support for the multidimensional perspective of self-concept and the reciprocal determinism of self-concept and performance (Marsh & Craven, 2006; Marsh & Hau, 2004; Marsh, Trautwein, Lüdtke, Koller, & Baumert, 2005). Moreover, such findings also fit well with work on the reciprocal determinism of self-efficacy and performance, the work by Williams and Williams (2010) in which Math self-efficacy and Math performance are mutually influenced across different nations and different cultures. This is in line with Bandura's (1986) contention that students form their feelings of self-efficacy that originated from previous performance such as past experiences of success or failure through attempts to solve tasks. Once formed, these beliefs will influence performance through the levels of persistence in the face of difficulties, the amount of effort exerted, and the choice of activities.

In addition, the current study also demonstrated that learning approaches and specific personality traits were reciprocally related with each other. The findings are consistent with previous Chinese and Western research (Chamorro-Premuzic & Furnham, 2009; Zhang, 2003) where personality and learning approaches had small-to-moderate correlations with each other. Of importance, our findings of the associations between learning approaches and personality traits were not restricted to concurrent correlations but were expressed in significant cross-lagged correlations. Specifically, those showing higher initial levels of adopting deep learning approaches exhibited accelerated increases in Openness and Conscientiousness, and accelerated decreases in Agreeableness; likewise, those showing lower initial levels of adopting surface learning approaches exhibited accelerated increases in

Conscientiousness. These cross-time links can be interpreted in terms of the sociogenomic model of personality (Robert & Jackson, 2008), assuming that environmental experiences influence personality traits in a bottom-up way and are likely to promote consistent changes in behavior at first (Roberts, 2009).

An Extension to the B5NT Model

Based on the aforementioned significant reciprocal effects, it can be assumed that from a longitudinal perspective, students' scholastic performance might also influence personality trait development via learning approaches and self-beliefs. Actually, the present research demonstrated two significant reverse longitudinal indirect effects from scholastic performance to Agreeableness and Conscientiousness via Math self-efficacy. For Conscientiousness, mathematics is well known to be a well-structured and sequential domain in that subsequent performance is also dependent on the achievement of preceding Mathematics courses. Thus, feedback from Mathematics exams might provides students with more clear information about their competences in Math learning (Singh, Granville, & Dika, 2002). As such, students scoring higher Math grades tend to develop higher levels of self-beliefs in their Math learning. According to the aforementioned bottom-up approach of personality development, consistent increases in students' self-beliefs in their Math learning might influence the development of Conscientiousness. For Agreeableness, one possible explanation could be due to the negative correlation between Agreeableness and Narcissism (Miller & Campbell, 2008; Miller & Maples, 2011). It seems that low Agreeableness is a central element of constructs such as narcissism. When students perform very well in Mathematics, they are inclined to develop more positive self-beliefs in the Mathematics learning. This in turn might feed feelings of superiority and thereby lead to an increase in narcissism, which is reflected in the decrease in Agreeableness. In contrast, there were no reverse longitudinal indirect effects observed in language subjects. This might be due to the fact that feedback pertaining to language performances may provide students with relatively more ambiguous information pertaining to their own competence. Thus, self-beliefs in language learning may not display the same level of predictive utility (Pietsch, Walker, & Chapman, 2003).

All in all, it is reasonable to extend the current B5NT model with reverse longitudinal indirect effects from students' scholastic performance (predictors) to narrow traits (mediators) to the Big Five (outcomes). We assumed that not only students' personality traits exert their influences on scholastic performance via narrow traits, but also students' scholastic performance affects personality trait development via narrow traits (see Figure 3). Specifically, the normal longitudinal indirect effects (i.e., personality traits → self-beliefs and learning approaches → scholastic performance) deepen our understanding of the specific mechanism by which personality traits affect scholastic performance. To some extent, the reverse longitudinal indirect effects (i.e., prior scholastic performance → self-beliefs and learning approaches → personality traits) specify a bottom-up approach of personality trait development (e.g., the sociogenomic model of personality). More importantly, this could be one part of future academic interventions since students' scholastic performance is more malleable than their personality traits. The intervening program should focus on the level of narrow traits. For example, providing reinforcement for students who adopt deep learning approaches or motivating students to create positive self-beliefs in their learning. In the short-term run, all of these might improve students' scholastic performance. In the long-term run, their scholastic performance might potentially contribute to personality maturation via these narrow traits, conversely again leading to the improvement of performance.

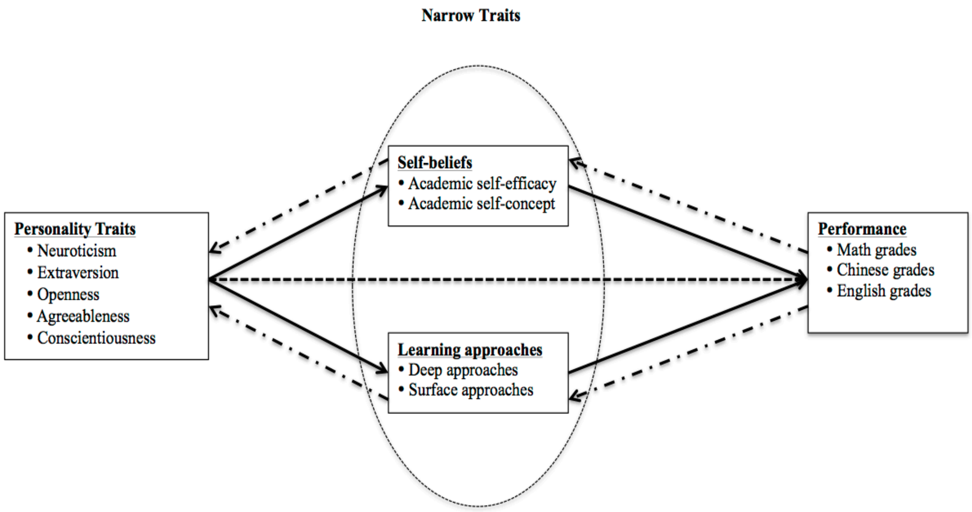


Figure 3. An extension to the B5NT model, assuming that students' scholastic performance also affects personality traits development via narrow traits.

Limitations and Directions for Future Research

Several limitations of this study need to be mentioned. First, this study relies on self-report measures of the Big Five and the narrow traits, which may lead to an overestimation of the associations among the variables. It would be desirable to collect both self-rated and other-rated reports in the future (Poropat, 2014; Ziegler et al., 2010). However, our study was based on a three-wave longitudinal design, which diminishes the risks for common method bias (Doty & Glick, 1998). Second, we measured each variable at three measurement points over a 1-year time span. The choice of spacing between measurement points might be too short to examine the hypothesized longitudinal indirect effects. However, a three-wave panel design as suggested by Cole and Maxwell (2003) is an improvement to cross-sectional designs, which make up the majority of studies. Moreover, a recent paper by Dormann and Griffin (2015) suggested that shorter time intervals could be beneficial in order to capture the maximum effect size across two waves of measurement. Of note, the cross-lagged effects and the longitudinal indirect effects found in this study were relatively weak. However, Zapf, Dormann, and Frese (1996) pointed out that it is very common to find small effects in longitudinal research because of the relatively high stability of the study variables. Despite the small effects, our results were still meaningful and supportive of the B5NT model. Last but not least, our sample differs with regard to age and gender. Though we included age and gender as control variables, it remains unclear whether the strength of specific indirect effects differs significantly between age and gender. Future research in a longer time span is needed to explore both age and gender differences in the assumed underlying processes. Otherwise, it cannot be ruled out that some of the effects increase or decrease with age.

In terms of that, more longitudinal research with varying time intervals, different samples, and different cultures is needed to better understand the specific mechanisms underlying the relationship between personality and scholastic performance. In addition, future studies should explore other important potential mediators (e.g., achievement goals, academic motivation, and effortful strategies) and consider multiple mediators simultaneously. As conceived with the sociogenomic model of personality (Roberts & Jackson, 2008), sustainable changes in personality traits may be predictive of consistent changes in behavior in a bottom-up fashion (see Bleidorn, 2012). Future research is needed to find the actual behavioral differences underlying these effects by the use of experience sampling. As mentioned before, our findings suggest an extension of the current B5NT model, which also demands more future research in different cultures and different samples to confirm whether students' initial scholastic performance influences their later personality trait development via narrow traits.

Conclusions

In conclusion, this study is one of the first to investigate the full longitudinal indirect of the relationship between the Big Five and scholastic performance in Math, Chinese, and English by motivation and learning approaches as suggested in the B5NT model. In addition, the specific mechanism underlying this bivariate relationship seems to be subject-specific.

Moreover, the present investigation provided empirical support for reciprocal influences of self-beliefs and scholastic performance on personality traits and learning approaches in a Chinese culture. Of importance, we also found two reverse longitudinal indirect effects in which those showing higher initial scholastic performance exhibited accelerated increases in Conscientiousness and decreases in Agreeableness. Last but not the least, our findings support the B5NT model and further specify an extension to it. Even though it is still premature, educators could develop some intervention programs to improve scholastic performances in combination with fostering students' self-beliefs in their learning and their personality.

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Appendix A

Table A. Zero-Order Correlations Between All The Variables Tested in This Study.

					T1 – T2											
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1.N	**(.83)**	-.36***	-.12*	.42***	-.42***	-.30***	.25***	-.28***	-.29***	-.11*	-.14**	-.07	-.12*	-.13**	-.06	-.02
2.E	-.38***	**(.81)**	.18***	-.27***	.25***	.32***	-.06	.18***	.18***	.15**	.22***	.14**	.15**	.08	.14**	.06
3.O	-.10*	.21***	**(.67)**	-.20***	.28***	.48***	-.23***	.26***	.35***	.16**	.24***	.20***	.27***	.25***	.21***	.29***
4.A	.38***	-.22***	-.11*	**(.63)**	-.33***	-.25***	.22***	-.09	-.11*	-.11*	-.16**	-.05	-.10*	.01	-.02	.07
5.C	-.43***	.25***	.26***	-.36***	**(.82)**	.50***	-.28***	.28***	.35***	.22***	.29***	.26***	.28***	.12*	.12*	.07
6.DA	-.30***	.32***	.46***	-.26***	.53***	**(.84)**	-.12*	.34***	.48***	.22***	.30***	.25***	.33***	.25***	.24***	.20***
7.SA	.24***	-.07	-.25***	.22***	-.27***	-.10*	**(.74)**	-.13**	-.21***	-.10*	-.14**	-.12*	-.16**	-.22***	-.22***	-.22***
8.SC_m	-.26***	.15**	.25***	-.09	.28***	.36***	-.15**	**(.88)**	.61***	-.20***	-.14**	-.01	-.02	.52***	.12*	.16**
9.SE_m	-.28***	.20***	.36***	-.13**	.38***	.50***	-.20***	**.64*****	**(.89)**	.09	.21***	.17***	.29***	.38***	.20***	.22***
10.SC_c	-.09	.15**	.15**	-.10*	.22***	.23***	-.07	-.22***	.07	**(.88)**	.68***	.13**	.23***	-.17**	.22***	-.01
11.SE_c	-.14**	.24***	.24***	-.17***	.31***	.33***	-.14**	-.13**	.26***	**.71*****	**(.92)**	.21***	.43***	-.11*	.21***	.05
12.SC_e	-.08	.14**	.18***	-.05	.26***	.25***	-.14**	.03	.22***	.12*	.22***	**(.88)**	.72***	.18***	.24***	.49***
13.SE_e	-.13**	.19***	.26***	-.11**	.31***	.35***	-.16**	.01	.36***	.23***	.46***	.76***	**(.93)**	.16**	.28***	.44***
14.Math	-.14**	.09	.22***	-.02	.17***	.29***	-.23***	.49***	.38***	-.16**	-.10*	.17***	.15**	---	.50***	.54***
15.Chinese	-.09	.17**	.23***	-.04	.10*	.20***	-.24***	.12*	.21***	.20***	.17**	.22***	.26***	.51***	---	.57***
16.English	-.03	.11*	.27***	.07	.07	.16**	-.24***	.17**	.23***	-.03	.02	.52***	.47***	.55***	.59***	---

					T2 - T3											
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1.N	(**.86**)	-.26***	-.10*	.34***	-.32***	-.22***	.20***	-.29***	-.26***	-.09*	-.05	-.01	-.04	-.03	.02	.01
2.E	-.37***	(**.82**)	.15**	-.13**	.27***	.21***	-.04	.11*	.16**	.12*	.16**	.10*	.15**	.08	.12*	.08
3.O	-.10*	.21***	(**.70**)	-.04	.25***	.37***	-.15***	.22***	.35***	.21***	.25***	.09*	.20***	.22***	.17***	.20***
4.A	.43***	-.28***	-.23***	(**.68**)	-.36***	-.33***	.24***	-.17**	-.27***	-.16**	-.14**	-.11*	-.11*	-.05	-.07	-.04
5.C	-.46***	.28***	.32***	-.43***	(**.83**)	.47***	-.22***	.29***	.35***	.23***	.22***	.22***	.22***	.10*	.09*	.11*
6.DA	-.31***	.33***	.50***	-.36***	.57***	**(.82)**	-.09*	.27***	.42***	.29***	.33***	.22***	.32***	.16**	.11*	.14**

7.SA	.26***	-.06	-.22***	.27***	-.30***	-.12*	(**.73**)	-.16**	-.14**	-.08	-.05	-.13**	-.10*	-.21***	-.16**	-.20***
8.SC_m	-.29***	.17**	.27***	-.23***	.29***	.37***	-.16**	(**.88**)	.55***	-.11*	-.11*	-.03	-.03	.34***	.10*	.12*
9.SE_m	-.29***	.19***	.37***	-.30***	.39***	.53***	-.22***	**.63*****	(**.89**)	.12*	.21***	.20***	.30***	.31***	.22***	.22***
10.SC_c	-.12*	.14**	.18***	-.12*	.25***	.27***	-.07	-.20***	.09	(**.88**)	.60***	.16**	.25***	-.08	.16**	.03
11.SE_c	-.15**	.21***	.24***	-.20***	.35***	.35***	-.10*	-.14**	.25***	**.75*****	(**.91**)	.22***	.39***	-.03	.19***	.06
12.SC_e	-.06	.16**	.18***	-.12*	.26***	.29***	-.13**	.02	.21***	.16**	.23***	(**.88**)	.62***	.19***	.17***	.43***
13.SE_e	-.11*	.19***	.25***	-.19***	.32***	.39***	-.15**	-.01	.35***	.28***	.46***	**.77*****	(**.93**)	.21***	.24***	.44***
14.Math	-.10*	.10*	.24***	-.10*	.14**	.26***	-.24***	.50***	.43***	-.17**	-.12**	.19***	.17**	---	.48***	.57***
15.Chinese	-.03	.13**	.20***	-.06	.12*	.22***	-.19***	.09	.20***	.20***	.19***	.27***	.30***	.52***	---	.48***
16.English	.02	.08	.25***	-.03	.07	.21***	-.19***	.14**	.25***	-.03	.02	.51***	.47***	.66***	.60***	---

					T1 - T3											
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1.N	(**.85**)	-.24***	-.12*	.32***	-.30***	-.20**	.19***	-.26***	-.27***	-.09	-.04	< .01	-.02	-.06	-.05	-02
2.E	-.39***	(**.80**)	.13**	-.14**	.22***	.19***	-.03	.08	.14**	.16**	.17***	.10*	.12*	.05	.11*	.05
3.O	-.12*	.18***	(**.69**)	-.02	.22***	.34***	-.15**	.22***	.34***	.22***	.24***	.13*	.21***	.22***	.16**	.22***
4.A	.42***	-.19***	-.18***	(**.67**)	-.33***	-.22***	.20***	-.06	-.10*	-.16**	-.14**	-.04	-.07	.02	-.03	.06
5.C	-.41***	.26***	.37***	-.37***	(**.83**)	.42***	-.15**	.25***	.28***	.19***	.19***	.19***	.20***	.11*	.09*	.09*
6.DA	-.23***	.21***	.53***	-.26***	.62***	(**.86**)	-.06	.23***	.37***	.25***	.25***	.20***	.25***	.12*	.13*	.10*
7.SA	.19***	.01	-.21***	.26***	-.18***	-.14**	(**.77**)	-.12*	-.10*	-.10*	-.09*	-.10*	-.07	-.20***	-.18***	-.22***
8.SC_m	-.29***	.09	.24***	.01	.31***	.30***	-.18***	(**.90**)	.54***	-.12*	-.10*	-.01	-.01	.35***	.12*	.15**
9.SE_m	-.26**	.17***	.41***	-.10*	.36***	.49***	-.15**	.64***	(**.90**)	.12*	.21***	.18***	.27***	.28***	.20***	.20***
10.SC_c	-.11*	.16**	.26***	-.19***	.27***	.34***	-.04	-.12*	.17**	(**.88**)	.53***	.14**	.21***	-.08	.20***	.05
11.SE_c	-.08	.23***	.28***	-.18***	.28***	.39***	-.08	-.10*	.31***	.74***	(**.91**)	.23***	.39***	-.01	.20***	.10*
12.SC_e	-.05	.10*	.15**	< .01	.18***	.27***	-.10*	.09*	.22***	.18***	.21***	(**.88**)	.60***	.22***	.18***	.43***
13.SE_e	-.06	.16***	.29***	-.04	.29***	.44***	-.12*	.07	.41***	.27***	.46***	.71***	(**.92**)	.20***	.25***	.41***
14.Math	-.10*	.02	.23***	.02	.15**	.21***	-.22***	.38***	.31***	-.08	-.06	.26***	.25***	----	.45***	.51***
15.Chinese	-.03	< .01	.16**	-.04	.12*	.17**	-.12*	.07	.20***	.18***	.19***	.18***	.28***	.55***	----	.49***
16.English	-.04	.02	.22***	.04	.09*	.21***	-.19***	.19***	.25***	.02	.05	.49***	.44***	.72***	.59***	----

Note. N ranges from 485 to 751. N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness; DA = Deep Approach; SA = Surface Approach; SC_m = Math self-concept; SE_m = Math self-efficacy; SC_c = Chinese self-concept; SE_c = Chinese self-efficacy; SC_e = English self-concept; SE_e = English self-efficacy. Reliability coefficients (Omega) for specific latent variables are in brackets on the diagonal. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. All P-values are two-tailed.

General Discussion

Educationalists and psychologists have sought various individual constructs related to scholastic performance for decades. Specific research questions have been proposed and discussed very often: What is the predictive power of intelligence and personality traits? Is the predictive power of intelligence and personality traits subject-specific? Are there any interaction effects between intelligence and personality traits in predicting scholastic performance? If so, are the interaction effects consistent across different school subjects? Why and how do students' personality traits influence their scholastic performance? Are the mechanisms subject-specific? Do the subject-specific mechanisms change over time? To answer these questions, this dissertation examined the interplay between students' Gf, broad personality traits, and other narrow constructs (i.e., learning approaches and self-beliefs). Empirical evidence was gathered in the context of 836 Chinese secondary school students.

The particular aim of this dissertation was to deepen our understanding of predicting scholastic performance in Chinese culture. The present chapter first summarizes the main findings presented in the specific studies of this dissertation (**Papers 1-3**), followed by describing limitations and proposals for avenues for future research. Lastly, implications and contributions to theory and research are discussed in more detail.

Summary of Main Findings

Paper 1 presented an examination of individual difference variables influences on scholastic performance in the context of Chinese secondary school students. The findings laid important groundwork for the explorations presented in **Papers 2 and 3**. For a more detailed discussion of these findings, the reader is invited to consult the respective papers directly.

(1) To what degree do students' Gf and personality traits predict their scholastic performance? Are these effects consistent across different school subjects (i.e., Mathematics, Chinese, and English)?

By using a combination of hierarchical regression analyses with ordinary least squares and structural equation modeling (SEM), **Paper 1** examined the predictive power of figural reasoning as an indicator of Gf and the Big Five on school grades. Analyses were conducted for different subjects (i.e., Mathematics, Chinese, and English) and for the composite of the three (grade composite). The ordinary least squares results were very similar to the SEM results. As expected, figural reasoning as an indicator of Gf predicted performance for all grades and for the composite. After controlling for age, gender, and Gf, the Big Five still contributed to the prediction of school grades, but their contributions varied according to school subjects. Specifically, Openness had a positive effect on performance for all subjects. For Conscientiousness, the effects were clearly smaller and, at the .05 level, only significant for Math. Neuroticism had a negative effect on Math grades. The effects of Extraversion on all grades were very small and not significant. Of note, Agreeableness did not predict significantly any school grades.

In general, the results of **Paper 1** replicated the specific effects for Gf and some of the personality domains on scholastic performance found in Western cultures in an Eastern culture. The results that differed may be related to how students learn Mathematics in comparison with language subjects. Mathematics is well known to be more difficult and to be more strongly associated with challenges, exam stress, and problem solving. A grasp of Mathematics requires students to devote sufficient time, effort, and a large amount of cognitive ability. Additionally, students tend to be afraid of Mathematics examinations, which might stimulate the feeling of anxiety. In contrast, language learning seems to be relatively easier; people learn their native language through everyday interactions, and what they have to learn has a higher degree of familiarity. English learning is more focused on an accumulation of vocabulary and grammar. The Chinese way of learning (i.e., rote-memorization) still fits very well with English learning (Ma & Kelly, 2009). This might also explain why there were no significant differential effects for a native language compared with a foreign language in the current study.

(2) Are there any interaction effects between intelligence and personality traits in predicting scholastic performance? If so, are the interaction effects consistent across different school subjects?

Besides the specific effects of figural reasoning as an indicator of Gf and the Big Five, **Paper 1** also explored their interaction in predicting scholastic performance. The results only supported the interaction hypothesis for Openness but not for Conscientiousness and Neuroticism. Hierarchical latent regression analyses indicated a compensatory interaction between Openness and figural reasoning for all school subjects: one of both traits is sufficient to perform well. As such, students high in Gf are able to handle school tasks even when they are not curious or seeking new knowledge. Similarly, students high in Openness may not need strong Gf because they are curious about different fields, actively grasping new ideas and seeking novel experiences.

The results further suggest that scholastic performance basically relies on the same mechanisms through the secondary school years. This is an important advance in understanding the relationships between individual difference variables and scholastic performance.

(3) Why and how do students' personality traits affect their scholastic performance? Are these mechanisms subject-specific?

Paper 1 clearly demonstrated that the Big Five significantly contributed to the prediction of scholastic performance independent of other variables. However, the specific mechanisms in this trait-performance relationship were still unclear. On the basis of the analysis level model of personality (see McAdams & Pals, 2006, for a review) and surface-core traits theory (Marsh & Craven, 2006), **Paper 2** conducted a cross-sectional study in which two theory-driven process models were tested against each other (i.e., the B5NT model vs. the DM model). Combined with previous preliminary evidence for the mediation processes (e.g., Corker, Oswald, & Donnellan, 2012; Hair & Graziano, 2003; Richardson & Abraham, 2009; Shams, Mooghali, & Soleimanpour, 2011), students' self-beliefs in their learning and approaches to dealing with study tasks are treated as potential mediators.

The results of **Paper 2** strongly supported the B5NT model, whereas the DM model was only supported for Conscientiousness and Openness (and this only in Mathematics). For all subjects, Conscientiousness (positive) and Openness (positive) influenced school grades indirectly through subject-specific self-concept. Openness (negative), Neuroticism (positive), and Extraversion (positive) exerted its indirect influences on school grades via a surface learning approach. On the subject-specific level, both Conscientiousness and Openness also had indirect effects on Math and English performance via a deep learning approach. Neuroticism had a negative indirect effect on Math grades via Math self-concept. Agreeableness failed to predict any of school grades.

(4) Do the subject-specific mechanisms change over time?

So far, evidence for the B5NT model has only been examined in a cross-sectional study. However, longitudinal support for the process model is still rare but needed because the proposed meditational processes should likely develop over time. To overcome this shortcoming, **Paper 3** further evaluated the B5NT process model in a three-wave longitudinal panel design over a time span of one year.

The results revealed that for all three subjects, Conscientiousness (negative) and Neuroticism (positive) exerted their longitudinal mediation effects on scholastic performance via a surface learning approach, even after controlling for age and gender. For Mathematics, more open and less neurotic students tended to develop more positive self-beliefs in their Math learning which, in turn, helped them to achieve higher Math performance. In addition, less agreeable students tended to create higher levels of self-efficacy in their Math learning, thereby leading to higher performance. For language subjects, Openness (positive), Conscientiousness (positive), and Agreeableness (negative) had significant longitudinal mediation effects on scholastic performance via a deep learning approach. Specifically for English, Neuroticism also had a negative longitudinal mediation effect on English grades via a deep learning approach. It seems that in the long-term, motivational aspects are more important for Math achievements, while learning approaches are more vital for language achievements.

(5) Additional findings

Above and beyond the expected effects, the three-wave panel study also found several significant reciprocal effects. For Math and English, students' school grades and their corresponding self-beliefs mutually influenced each other. Moreover, these effects occurred through the entire school year and were stable over time. Additionally, learning approaches and personality traits were reciprocally related to each other. Specifically, those showing higher initial levels of adopting deep learning approaches exhibited accelerated increases in Openness and Conscientiousness as well as accelerated decreases in Agreeableness; likewise, those showing lower initial levels of adopting surface learning approaches exhibited accelerated increases in Conscientiousness. Moreover, we also found two reverse longitudinal mediation effects from scholastic performance to Agreeableness and Conscientiousness via Math self-efficacy. That is, students who performed very well in Mathematics tended to develop higher levels of self-beliefs in their Math learning. In turn, consistent increases in students' self-beliefs in their Math learning might trigger the maturation of Conscientiousness. It is likely that students who have relatively good Math grades might in turn develop feelings of superiority and thereby increase their narcissism, which would be reflected in the decrease in Agreeableness (Miller & Campbell, 2008; Miller & Maples, 2011).

Limitations of the Current Dissertation and Directions for Future Research

Although this dissertation has consistently supported the expected links among and between its focal variables, several limitations need to be mentioned that warrant more attention in future research. First, the specific measures of Gf and personality traits have solely focused on a broader domain level. There is, for example, strong support that lower-order sub- facets are useful for the prediction of educational performance (e.g., Chamorro-Premuzic & Furnham, 2003; De Fruyt & Mervielde, 1996; Gray & Watson, 2002; see O'Connor & Paunonen, 2007, for a review). However, as is often the case in field studies, we had to come to a compromise between keeping test length within reasonable boundaries and having more narrow traits possible with higher predictive power. Future studies should assess specific lower-order facets of personality and intelligence to shed more light on their impact on scholastic performance. Of most importance, we can take a facet perspective to provide new insights into the moderation and mediation processes that govern the prediction of scholastic performance.

Second, the moderation processes (i.e., Gf * the Big Five) were only explored in a cross-sectional study, so little is known about their stability and change over time. The mediation processes underlying the relationships between the Big Five and scholastic performance has been supported in both cross-sectional and longitudinal research design. Moreover, we measured each variable at three measurement points over a time span of one year. However, The choice of the time interval might be too short to examine the hypothesized longitudinal mediation effects. A recent study by Dormann and Griffin (2015) suggested that in cross-lagged studies, using shorter time intervals than one year might be beneficial to unravel change processes. As such, more future research with varying time intervals, different samples, and even different cultures is needed to better understand the specific mechanisms.

Third, all the studies presented in this dissertation were restricted to a macro-analytical level; this left the specific processes on a micro-analytical level unknown. Prior research demonstrated that individual differences constructs contributed to the prediction of educational performance and also manifested themselves through behavior (Bleidorn, 2012; Paunonen & Ashton, 2001). Moreover, Conard (2006) identified attendance behavior that mediated the relationship between Conscientiousness and academic performance. Therefore, in order to better understand the specific mechanisms and behaviors involved in the interplay this work focused on, future research should collect experience sampling data on a day-to-day basis. As such, it is possible to assess differences in behavior and experiences and, ultimately, to investigate whether the specific behavior and experiences can explain mechanisms on the macro level as outlined above.

Contributions and Implications of the Current Dissertation

Direct contributions. On a general level, the current dissertation extended prior research in at least three ways. First, the sample used here included Chinese secondary school students, which so far have not received much interest. This dissertation provided evidence for the prediction of scholastic performance in Chinese culture and replicated most findings derived from Western research. Second, it extends previous research on the specific effects of intelligence and personality traits in predicting scholastic performance by zooming into the underlying processes. The results suggest that intelligence and personality traits, specifically Openness, compensated for the lack of each other in predicting scholastic performance. Moreover, the results from both a concurrent and longitudinal study also deepen our understanding of the specific mechanisms underlying the trait-performance relationship as well as its stability and change over time. Third, this dissertation attempted to provide a preliminary framework illustrating the routes to scholastic performance: intelligence and personality traits were, as the framework specified, empirically established as important predictors of scholastic outcomes. Additionally, this work yielded important first insights into the moderation and mediation processes. However, future research should flesh out the framework more.

"Big Picture" contributions and ideas for further research developments. As mentioned before, the current dissertation provided a coherent framework for the prediction of scholastic performance, and it also opened a door for future research developments. We did not explore the specific mechanisms underlying the relationship between intelligence and scholastic performance, which merits future attention. For example, important but not yet sufficiently answered questions remain: What about the mediating roles of self-beliefs and learning approaches in this relationship? How about the other motivation system like academic interest? Chamorro-Premuzic and Furnham (2008) found that deep learning approaches mediated the effects of IQ on academic performance, suggesting that IQ led to higher academic performance because individuals with a higher IQ employed more deep learning approaches. Likewise, Pajares and Kranzler (1995) found that ability and self-efficacy had strong direct effects on Math performance and self-efficacy mediated the indirect effect of ability on performance. Furthermore, Silvia and Sanders (2010) found that Gf was associated with finding things more interesting in both poems and picture. It seems reasonable that, just as the Big Five traits, Gf might also affect scholastic performance via narrow traits (e.g., self-beliefs, academic interest, and learning approaches).

In addition, this work first attempted to integrate previous research into the two process models (the B5NT and DM models) to explain why personality traits affect scholastic performance. Both a cross-sectional and longitudinal study provided strong evidence for the B5NT model. However, we mainly emphasized the mediating roles of self-beliefs and learning approaches. Instead, Corker et al. (2012) examined achievement goals and effort strategies as mediators that might explain why students with higher levels of Conscientiousness are predicted to achieve better academic performance. Both findings from different cultures and different samples not only confirmed the B5NT model, but also provided initial evidence for the DM model (i.e., Conscientiousness → Mastery approach → effort strategies → exam performance: see Corker et al' study; Openness/Conscientiousness → Math self-efficacy → deep approaches → Math grades: see **Paper 3**). Unfortunately, Corker et al.' study only focused on one of the Big Five domains and failed to explore the specific psychological processes for different school subjects. Likewise, the current dissertation failed to examine the DM model in a longitudinal perspective because of a three-wave panel study design. To fill in these gaps, future projects including all Big Five domains, other potential mediators, and more waves can be developed to examine the generalizability of the B5NT and DM model.

Lastly, we assumed that students' personality traits affect their scholastic performance via narrow traits. The significant normal longitudinal mediation effects (i.e., personality traits → self-beliefs and learning approaches → scholastic performance) deepen our understanding of the specific mechanisms. However, additional findings further indicated that students' scholastic performance might conversely affect their personality traits development via narrow traits. To some extent, the reverse longitudinal mediation effects (i.e., prior scholastic performance → self-beliefs and learning approaches → personality traits) specify a bottom-up approach of personality traits development (e.g., the sociogenomic model of personality: Robert & Jackson, 2008). Taken together, the aforementioned conceptual framework illustrating the prediction of scholastic performance should be tested in different culture, different samples, and also different school subjects (see Figure 1).

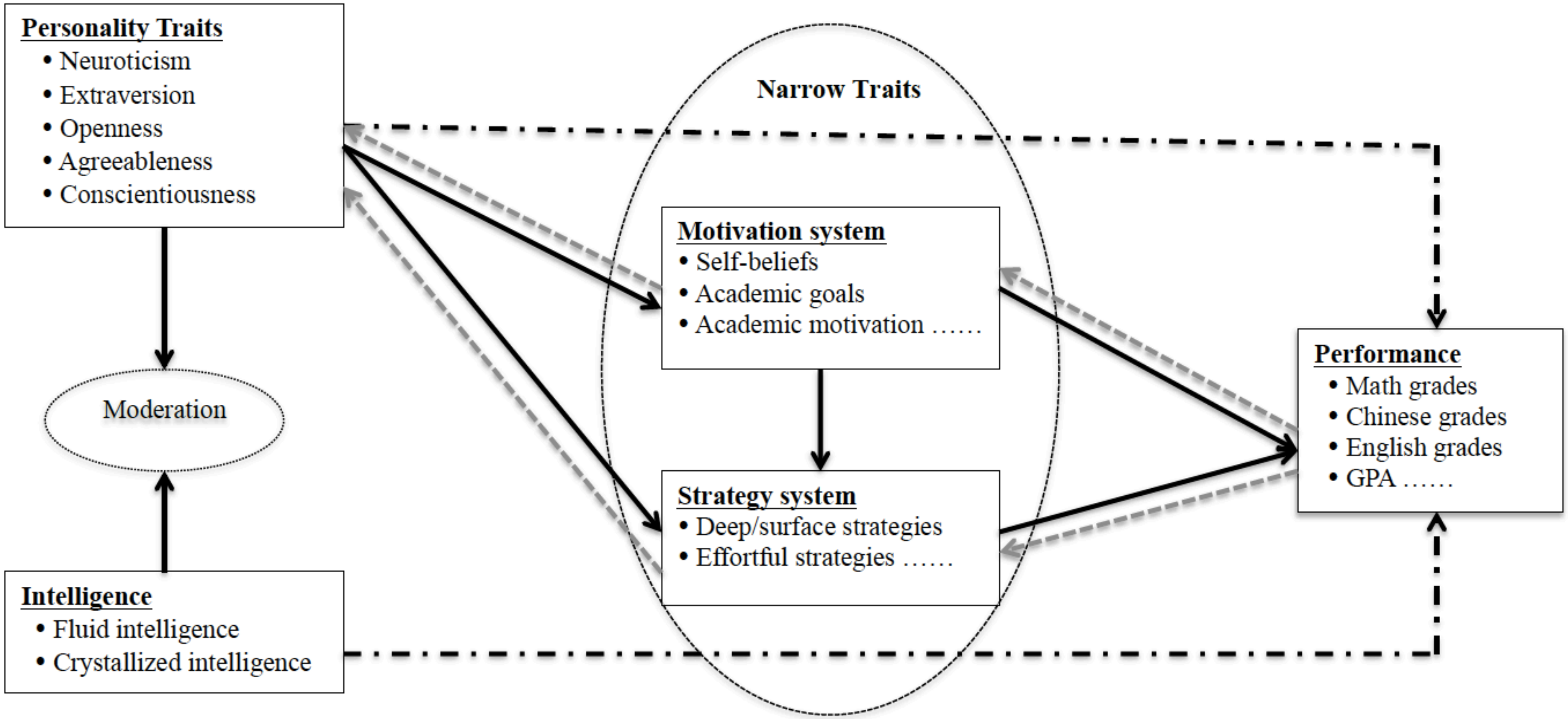

Figure 1. An extended model for the prediction of scholastic performance. *Note.* Oval shapes represent the central moderation and mediation processes that underlie the relationships between personality traits and scholastic performance. GPA = grade point average. We assumed that not only students' personality traits exert their influences on scholastic performance via narrow traits, but also students' scholastic performance affects their personality traits development via narrow traits (i.e., motivation and strategy systems).

Practical implications. The findings of this work not only enhance our understanding of the relationships between individual difference variables and scholastic performance but also provide important practical implications. First, knowledge of factors related to scholastic performance allows educators to identify individuals who will, and individuals who will not, perform well in specific school subjects. This may lead to advancements in developing fair students-oriented academic programs to help those who have problems in their learning. Second, this work examined the complex interplay between intelligence, personality traits, and other narrow traits and thereby established a preliminary causal direction of the effects on scholastic performance. The findings indicate that it might be useful for educational counselors to facilitate achievement-oriented personality development and modify achievement-hindering traits in the hope of promoting students' scholastic performance. Personality traits are barely believed to be changed (McCrae & Costa, 1994; Roberts & DelVecchio, 2000) but operate through behaviors (Bleidorn, 2012; Paunonen & Ashton, 2001). According to Roberts and Jackson's (2008) sociogenomic model of personality, consistent behavioral change might lead to personality traits change. As such, identifying a set of specific behaviors reflected in certain personality traits could be a target of intervention programs designed to improve scholastic performance. For example, the significant reciprocal effects between deep learning approaches and Openness and Conscientiousness presented in this dissertation indicate that it might be useful for teachers to stimulate students' academic behavior of deploying more deep learning approaches to solve their school tasks. In the process of accomplishing their learning tasks through using deep learning approaches, students may develop along the Conscientiousness and Openness personality dimensions. Thirdly, two significant reverse longitudinal mediation effects presented in this dissertation further suggest an extension to the B5NT model in which students' prior scholastic performance might also influence their later personality traits development through narrower traits. This could be one part of future academic interventions since students' scholastic performance is more malleable than their personality traits. The intervening program should focus on the level of narrow traits. It might also be helpful for teachers to provide reinforcement for students who adopt deep learning approaches or to design intervention programs for developing students' positive self-beliefs in their learning. In the short-term run, all of these interventions might improve students' scholastic performance. In the long-term run, the students' scholastic performance might potentially contribute to personality maturation via narrow traits, and this process may again lead to the improvement of scholastic performance.

Conclusions

In conclusion, the specific studies presented in this dissertation have produced encouraging results. In the context of Chinese secondary school students, the findings replicated the specific effects of Gf and the Big Five on scholastic performance found in Western cultures. In addition, this work extended the unique effects of Gf and the Big Five to all three subjects (i.e., Mathematics, English, and Chinese). Furthermore, figural reasoning as an indicator of Gf interacted with Openness in the prediction of scholastic performance. Although a high level of Gf is believed to be positive, this beneficial effect is diminished or even reversed if students scored high on Openness. Moreover, broad evidence for the mediation mechanism that govern the prediction of scholastic performance was found in a cross-sectional and longitudinal study. Beyond the knowledge of the specific mechanism, the findings presented in **Papers 2 and 3** suggested that narrow constructs such as self-beliefs and approaches to learning can be the targets for academic interventions. Because they are more malleable than personality traits, they therefore translate into higher levels of scholastic performance more readily.

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